Smart Factory Layout Design Using Machine Learning Algorithms: An Appraisal of Methods and Digital Infrastructure

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Abstract

This study evaluates machine learning methods for smart factory layout design under Industry 4.0 requirements. Classical approaches based on heuristics, mathematical programming, and simulation provide decisions for bounded cases, yet performance declines as facility scale, connectivity, and disturbance driven variability increase. Supervised learning supports screening by predicting layout performance indicators, including throughput, cycle time, and energy related outcomes, reducing repeated full simulation for each alternative. Unsupervised learning reveals structure in sensor and operational data through clustering, dimensionality reduction, and anomaly detection, improving zone formation and monitoring for evolving layouts. Reinforcement learning enables sequential decisions in simulated or digital twin environments through reward driven policies tied to flow efficiency and reconfiguration under demand volatility. Hybrid models combine learning with metaheuristics to explore large combinatorial spaces and manage multi objective tradeoffs. Reported benefits include reduced travel distance, reduced material handling burden, improved space utilization, faster evaluation of design options, and improved flexibility during product mix changes. Limitations persist. Deep reinforcement learning and simulation assisted pipelines impose a high computational cost. Transfer across plants and product families remains inconsistent. Interpretability gaps restrict governance and shop floor trust. Deployment readiness depends on data quality, interoperability, latency, and security across IoT, MES, ERP, and digital twin stacks. Sustainability outcomes require explicit inclusion in objective functions. Future research should prioritize transferable policies, surrogate assisted training, edge-based inference, human guided co-design workflows, explainability evaluation, and integration with federated learning and quantum-oriented optimization concepts.

Keywords: *Smart factory; Facility layout planning; Machine learning; Digital twin; Reinforcement learning*

INTRODUCTION

Background on Smart Factories

Smart factories sit at the core of Industry 4.0, representing production environments where cyber-physical systems (CPS), the Internet of Things (IoT), and advanced analytics converge to deliver highly connected, automated, and adaptive manufacturing (Ghobakhloo, 2018; Ortt *et al.*, 2020; Shi *et al.*, 2020). This convergence is characterized by the integration of physical processes with digital systems, enabling real-time data capture, intelligent decision-making, and seamless coordination across the factory floor and beyond (Ghobakhloo, 2018; Ortt *et al.*, 2020). In this vision, digital technologies do not merely automate isolated tasks but create an interconnected ecosystem in which production can be monitored, controlled, and continuously optimized across time and space (Shi *et al.*, 2020; Ortt *et al.*, 2020).

Central to this ecosystem are digital twins, virtual representations of physical assets, processes, and systems that provide real-time visibility into operations, enable predictive insights, and support experimentation without disrupting the live operation. Digital twins enable testing of alternative strategies, configurations, and layouts in a safe, simulated environment before committing to changes on the shop floor (Nwamekwe *et al.*, 2025c; Kalsoom *et al.*, 2020). As a result, factories can validate designs and operational plans, anticipate performance under varying conditions, and shorten the cycle from concept to implementation (Nwamekwe *et al.*, 2025c; Kalsoom *et al.*, 2020). The concept of digital twins in manufacturing has evolved with ongoing work to identify research issues and implementation considerations for CPS-based production systems (Nwamekwe *et al.*, 2025g).

Beyond the CPS and digital-twin foundation, smart factories leverage data-driven analytics to optimize performance, maintenance, and decision-making. The industry 4.0 paradigm is underpinned by massive data generation from sensors, machines, and processes, emphasizing the role of AI and analytics in turning data into actionable intelligence for process optimization and predictive maintenance (Ghobakhloo, 2018; Ortt *et al.*, 2020). The literature highlights that advances in sensing technologies, data fusion, and analytics are critical enablers of these capabilities, supporting both the visibility of the current state and the forecasting of future states of the production system (Kalsoom *et al.*, 2020; Shi *et al.*, 2020).

Automation trends are redefining how manufacturing systems are designed, monitored, and optimized. Collaborative robotics or cobots, robots that collaborate with humans on shared tasks are increasingly integrated into production environments to augment human capabilities, improve safety, and enable more flexible workflow configurations (Igbokwe *et al.*, 2024). In addition, autonomous mobile robots (AMRs) and automated guided vehicles (AGVs) are enabling dynamic, task-driven routing and material handling on the factory floor; recent work demonstrates how multi-agent and swarm-like approaches can optimize fleet coordination and task allocation in Industry 4.0 contexts. These automation trends are closely tied to the emergence of edge computing and AI-driven decision support, which push computation closer to data sources and enable real-time analytics and control at scale (Kim *et al.*, 2021), with edge intelligence becoming a key enabler for responsive manufacturing environments (Kim *et al.*, 2021).

Edge computing and cloud/edge fog cloud integration play pivotal roles in delivering timely insights and scalable services within smart factories. The combination of edge computing with AI enables rapid, local inference and autonomous decision-making, reducing latency and bandwidth requirements while supporting robust operation in dynamic environments (Kim *et al.*, 2021). Studies discuss the design of smart manufacturing service systems that distribute computation across edge, fog, and cloud layers to support data-intensive applications, predictive analytics, and cross-site coordination (Vitalis *et al.*, 2024). These architectural patterns are recognized as essential for achieving scalable, resilient, and responsive smart factories in practice (Ortt *et al.*, 2020).

Despite the promise, the adoption of smart factory technologies faces notable challenges. Empirical work has identified barriers often centred on hardware readiness, data-management capabilities, and organizational or strategic factors that impede large-scale deployment of Industry 4.0 solutions (Xing *et al.*, 2022; Ortt *et al.*, 2020). Broader reviews emphasize the need for coherent implementation frameworks, maturity models, and governance structures to manage the transition to Industry 4.0-enabled production (Ortt *et al.*, 2020; Herrmann *et al.*, 2022). In particular, several studies highlight the risk that hardware and interoperability issues can dominate early-stage deployment in many facilities, especially SMEs, unless appropriate support and standards are in place (Xing *et al.*, 2022). Nevertheless, cross-industry and cross-region analyses suggest that a gradual, modular progression, often starting with pilots, digital-twin validation, and incremental data-fuelled improvements can help organizations realize Industry 4.0 benefits while managing risk (Ortt *et al.*, 2020; Herrmann *et al.*, 2022).

The smart factory concept is increasingly being studied across domains, with reviews and empirical work examining its drivers, architectures, and practical trajectories. Comprehensive syntheses describe how Industry 4.0 technologies CPS, IoT, cloud/fog/edge computing, AI, and CPS-based data ecosystems haven't yet produced a single universal blueprint but rather a set of architectures and best practices tailored to contexts such as European research programs and cross-sector deployments (Okpala *et al.*, 2025a; Ortt *et al.*, 2020). In addition, several domain-specific studies illustrate how smart factory principles manifest in different industries and settings, reinforcing the view that smart factories are not a one-size-fits-all solution but a flexible, technology-enabled approach to modern manufacturing (Okpala *et al.*, 2025c).

In short, smart factories embody the industry 4.0 ideal of highly integrated, data-driven, and autonomous production systems that leverage CPS, IoT, digital twins, edge computing, and AI-enabled decision support to optimize design, monitoring, and operation. They rely on real-time data and virtual representations to validate and refine layouts and processes before physical deployment, while automation trends ranging from cobots to AMRs and AI-driven planning reshape how factory layouts are conceived, validated, and continuously improved (Ghobakhloo, 2018; Nwamekwe *et al.*, 2025e; Shi *et al.*, 2020; Udu *et al.*, 2025; Kim *et al.*, 2021; Kalsoom *et al.*, 2020; Okpala *et al.*, 2025b; Xing *et al.*, 2022).

Importance of Factory Layout Design

Factory layout design is a fundamental determinant of production efficiency, operational costs, and system flexibility (Putri and Dona, 2019; Onyeka *et al.*, 2024). An optimal layout minimizes material handling time and energy consumption while improving safety and throughput (Ezeanyim *et al.*, 2025b; Ishak *et al.*, 2020). In smart manufacturing, rapid product customization and demand fluctuations necessitate agile, scalable layouts that maintain resource efficiency (Tarigan *et al.*, 2019; Nwamekwe *et al.*, 2025b). Digital twins enable real-time monitoring and virtual testing of layouts before physical deployment, accelerating validation and reducing disruption. Edge computing and AI-driven decision support enhance real-time analytics for adaptive layout management across the plant and supply chain (Kim *et al.*, 2021; Vitalis *et al.*, 2024).

Motivation for Using Machine Learning

Traditional factory layout design methods have historically relied on heuristic reasoning, classical optimization, or simulation-based approaches to determine the relative placements of facilities, workstations, and material-handling links. Examples from the literature show extensive use of systematic layout planning (SLP), multi-stage optimization, and other conventional methods to improve throughput and reduce waste (Putri and Dona, 2019; Lista *et al.*, 2021; Ishak *et al.*, 2020). While these methods can yield effective solutions in well-bounded and stable environments, they often struggle to scale to large, highly interconnected facilities and adapt to rapid reconfigurations driven by demand volatility and product customization (Putri and Dona, 2019; Lista *et al.*, 2021; Ishak *et al.*, 2020). Moreover, many traditional techniques treat layout design as a single-shot optimization problem, with limited capacity to incorporate real-time data streams or transparently balance multiple, potentially conflicting objectives such as cost, energy use, lead times, and safety (Tarigan *et al.*, 2019). The broader Industry 4.0 context underscores these limitations, highlighting the need for more scalable, data-driven, and adaptive approaches to layout design in modern manufacturing ecosystems (Ortt *et al.*, 2020).

Traditional methods also rely on static representations of processes and flows, which can become outdated as product mixes evolve or as autonomous systems alter material movements on the shop floor (Putri and Dona, 2019; Ishak *et al.*, 2020). The literature on dynamic facility layout planning (DFLP) and zone-based multi-objective layouts illustrates a push toward methods that account for changing conditions and uncertainty; however, these approaches often require substantial domain expertise and bespoke modelling efforts that limit transferability across facilities (Tarigan *et al.*, 2019). Recognizing these gaps, researchers have begun to explore data-driven, learning-based paradigms that can learn from historical and live data to propose, validate, and adjust layouts in ways that traditional deterministic methods cannot (Klar *et al.*, 2023).

Machine learning (ML) offers a complementary and increasingly attractive set of capabilities for layout design in smart factories. First, ML provides a data-driven foundation in which models learn structure, dependencies, and typical patterns directly from historical and sensor data, reducing reliance on manually crafted heuristics and static assumptions (Sonta *et al.*, 2021). This enables layout reasoning that better captures complex, nonlinear relationships among material flows, processing times, and resource constraints. Second, ML supports continual adaptation: models can incorporate streaming data to adjust or reconfigure layouts as conditions change, supporting agility in highly dynamic production environments (Nwamekwe *et al.*, 2025d; Udu *et al.*, 2025; Klar *et al.*, 2023). Third, ML is well-suited to multi-objective settings, where trade-offs among throughput, cost, energy, reliability, and safety must be balanced; learning-based approaches can identify Pareto-optimal strategies and provide scalable guidance across large problem instances (Klar *et al.*, 2023). Fourth, the convergence of ML with digital twins and edge computing enables safe, data-driven experimentation and fast, localized inference to support layout decisions without imposing disruptive changes on the live line, thus accelerating validation and deployment cycles (Nwamekwe *et al.*, 2025a; Udu *et al.*, 2025). Collectively, these capabilities position ML as a powerful enabler for design under uncertainty, rapid reconfiguration, and scalable optimization in modern smart factories (Ghobakhloo, 2018; Ortt *et al.*, 2020; Shi *et al.*, 2020; Nwamekwe *et al.*, 2020; Klar *et al.*, 2023; Sonta *et al.*, 2021).

The rationale for adopting ML in factory layout design is further reinforced by the ongoing development of Industry 4.0 technologies. Digital twins, virtual representations of physical assets and processes provide a unified framework for collecting, simulating, and validating layout configurations under diverse scenarios, enabling data-driven experimentation before physical changes are made on the shop floor (Nwamekwe *et al.*, 2025d). Edge computing and edge intelligence enhance analytics by reducing latency and supporting real-time decision-making critical for dynamic layout adjustments, especially in facilities with mobile robots and fluctuating demand (Kim *et al.*, 2021; Vitalis *et al.*, 2024). The broader body of Industry 4.0 research emphasizes that while adoption presents challenges, a gradual, modular progression aided by data-driven approaches can yield substantial benefits while managing risk (Ortt *et al.*, 2020; Xing *et al.*, 2022; Herrmann *et al.*, 2022). Within this context, ML-enabled layout design presents a pathway to scalable, adaptive, and transparent optimization that aligns with the agile, data-rich posture of smart factories (Ghobakhloo, 2018; Ortt *et al.*, 2020; Shi *et al.*, 2020; Klar *et al.*, 2023).

Beyond pure performance gains, ML-driven layout design supports the practical realities of modern manufacturing, such as integrating with autonomous material-handling fleets and reconfigurable work environments. Recent work demonstrates that reinforcement learning (RL) and other simulation-based ML methods can yield transferable, multi-objective layout policies that scale with problem size and adapt to new facility configurations, providing an alternative to purely hand-crafted optimization pipelines (Klar *et al.*, 2023). In parallel, data-driven studies in adjacent domains such as energy-efficient or space-efficient facility design illustrate the broader value of learning-based layouts for reducing energy use, improving space utilization, and balancing competing objectives under uncertainty (Sonta *et al.*, 2021). The convergence of ML with digital twins and edge-based analytics thus provides a coherent foundation for exploring, validating, and deploying ML-driven layout strategies in Industry 4.0 settings (Nwamekwe *et al.*, 2025f; Klar *et al.*, 2023; Sonta *et al.*, 2021).

Scope and Objectives of This Review

This paper reviews recent progress in applying machine learning algorithms to smart factory layout design. It first examines classical approaches and their limitations, then explores how supervised, unsupervised, reinforcement learning, and hybrid models address these challenges. The review also highlights the role of data infrastructure, case studies, benefits, limitations, and future directions. The objective is to provide researchers and practitioners with a comprehensive understanding of how machine learning can drive intelligent and resilient layout design in smart factories.

FOUNDATIONS OF FACTORY LAYOUT DESIGN

Classical Layout Design Approaches

Historically, factory layout design has been advanced through three broad families of methods: heuristics, mathematical programming, and simulation-based techniques. Heuristic approaches provide practical, generally fast solutions by encoding organizational knowledge and layout relationships into reusable rules or procedures. Early systematic heuristics such as Systematic Layout Planning (SLP), BlocPlan, and Activity Relationship Chart (ARC) have dominated practice in many industries, offering structured pathways to generate feasible layouts without solving complex optimization problems from first principles (Preeti and Meena, 2024; Bassim and Al-Kindi, 2020; Onyeka *et al.*, 2024). In parallel, mathematical programming introduced more rigorous formulations for layout problems, aiming to produce optimal or near-optimal designs under multiple constraints, though these formulations can become computationally burdensome for large-scale facilities (Herrmann *et al.*, 2022). Finally, simulation-based techniques enabled dynamic analysis of layout choices under stochastic flows and changing conditions, supporting "what-if" experimentation that classical analytic methods alone cannot easily deliver (Ronde *et al.*, 2023; U-Dominic *et al.*, 2025).

Heuristic approaches remain foundational because they translate domain expertise into repeatable design processes and typically yield workable layouts with modest data and computational demands. Systematic Layout Planning (SLP) is a representative workflow among these heuristics; it structures the design process around relationships and proximities among departments and activities, guiding practitioners from relationship data to concrete floor plans and material-flow considerations (Preeti and Meena, 2024; Bassim and Al-Kindi, 2020). Several empirical studies document the practical uptake of SLP across industries, including manufacturing lines and process facilities, and show how SLP-based designs can achieve substantial improvements in space utilization and flow efficiency when coupled with subsequent refinements or cross-checks (Preeti and Meena, 2024; Bassim and Al-Kindi, 2020). In addition to SLP, BlocPlan has been deployed as a complementary heuristic to explore alternative layouts by combining block-based representations with planner-style reasoning, illustrating how hybrid heuristic pipelines can improve design throughput and quality (Putri and Dona, 2019; Preeti and Meena, 2024). Collectively, these heuristic families emphasize structural thinking about adjacency, material flow, and process steps while keeping the design process accessible to practitioners without requiring heavy optimization modelling (Lista *et al.*, 2021; Ezeanyim *et al.*, 2025a).

ARC-based methods often used to quantify and leverage interdependencies between activities are another important heuristic tradition in classical layout practice. ARC-driven layout studies focus on the strength of relationships among activities to drive proximity decisions, with subsequent evaluation of total material handling costs and flow distances. Contemporary works continue to demonstrate ARC-based reasoning as a practical means to capture qualitative and quantitative relationships in a way that remains tractable for medium-scale facilities. The ARC paradigm thus exemplifies how a relatively lightweight, information-rich representation can support rapid iteration and intuitive interpretation of layout options, especially in contexts where detailed flow models are costly or unavailable.

ALDEP (Automated Layout Design Program) illustrates a different lineage within classical heuristics, offering algorithmic guidance that systems can use to assemble layouts by considering pairwise relationships and relational weights. While ALDEP embodies a more prescriptive procedural logic than ARC or SLP, it remains a foundational example of how heuristic reasoning can be translated into computational design steps that yield repeatable, auditable layouts. Studies describing ALDEP and similar rule-based design approaches underscore their continued relevance for designers requiring transparent, auditable decision rules in facilities with clear relational structures (Herrmann *et al.*, 2022).

Mathematical programming introduced a more formal optimization lens to factory layout problems. Classical exact formulations often framed as mixed-integer programs or related combinatorial models aim to identify globally optimal layouts subject to material flows, processing times, and spatial constraints. While exact methods deliver strong theoretical guarantees, their computational burden grows quickly with problem size and complexity, which has historically limited their direct applicability to very large or highly dynamic facilities. Several reviews of production planning and control under Industry 4.0 contexts discuss the migration from ad hoc heuristics to more formal optimization paradigms, highlighting the tension between solution quality and computational scalability (Herrmann *et al.*, 2022). This tension motivates hybrid approaches in modern practice, where exact methods may be used for subproblems or smaller zones within a larger, more complex design task (Herrmann *et al.*, 2022).

Simulation-based techniques add a complementary dimension by enabling dynamic experimentation with layout configurations under realistic, often stochastic, operating conditions. Static assessments of layout quality give way to dynamic simulations that model material flows, inventory levels, and resource utilization over time. Advances in discrete-event simulation and integrated design environments have made simulation-based exploration more accessible. Contemporary studies demonstrate that simulation can support layout decisions during design phases, allowing analysts to compare candidate layouts under varied demand scenarios, product mixes, and process changes before committing to physical changes on the shop floor (Ronde *et al.*, 2023; U-Dominic *et al.*, 2025). This progression from static heuristics to dynamic, data-driven evaluation captures a central development trend in classical layout foundations and foreshadows the data-centric, ML-enabled approaches that follow.

Across these three families, several recurring themes emerge. First, classical approaches emphasize adjacency, flow efficiency, and space utilization as primary objectives, often balancing these with handling costs, safety, and flexibility constraints (Putri and Dona, 2019; Lista *et al.*, 2021; Ezeanyim *et al.*, 2025a). Second, the practicality and interpretability of heuristics make them robust choices for many real-world settings, especially where data are limited or where rapid iteration is essential (Lista *et al.*, 2021; Ezeanyim *et al.*, 2025a); Preeti and Meena, 2024). Third, the growth of data, connectivity, and computational power gradually elevates mathematical programming and simulation as complementary or hybrid components, enabling more rigorous or dynamic analyses while preserving tractability in practice (Herrmann *et al.*, 2022; Ronde *et al.*, 2023; U-Dominic *et al.*, 2025). These foundations collectively frame today's dialogue on machine-learning-driven layout design, where ML aims to extend the capabilities of these classical approaches by learning patterns from data, handling multi-objective trade-offs, and supporting real-time adaptation within digital-twin-enabled environments (Herrmann *et al.*, 2022; Klar *et al.*, 2023).

Challenges in Traditional Methods

Classical factory layout design has historically relied on three broad families of methods: heuristics, mathematical programming, and simulation-based techniques. Heuristic approaches provide practical, often rapid, solutions by embedding domain knowledge and relational proximity rules into repeatable procedures (Putri and Dona, 2019; Lista *et al.*, 2021). While such heuristics are appealing for their interpretability and low data requirements, they frequently yield suboptimal results for complex, modern layouts and can struggle to scale to large, high-dimensional problems (Putri and Dona, 2019; Lista *et al.*, 2021). The continued prominence of heuristic methods in practice is documented, but their limitations in the face of increasing system complexity motivate the search for more data-driven alternatives (Herrmann *et al.*, 2022; Lista *et al.*, 2021).

Mathematical programming introduces a rigorous optimization lens to layout problems, typically culminating in mixed-integer or related formulations designed to identify globally optimal designs under material-flow, processing time, and spatial constraints. However, the computational burden of exact approaches grows rapidly with problem size and complexity, limiting their direct applicability to large, dynamic facilities common in Industry 4.0 contexts (Herrmann *et al.*, 2022). Consequently, many studies advocate hybrid architectures that employ exact subproblems or smaller-zone optimizations within a broader, heuristic or data-driven framework to retain tractability while improving solution quality (Herrmann *et al.*, 2022; Tarigan *et al.*, 2019).

Simulation-based techniques offer a complementary capability by enabling dynamic experimentation with layout configurations under realistic, stochastic operating conditions. Discrete-event or integrated design simulations allow analysts to compare candidate layouts across varying demand scenarios, product mixes, and process changes before committing to physical changes (Ronde *et al.*, 2023). Nevertheless, these simulation-based explorations can be time-consuming and require skilled operators to build and validate models, hindering rapid iteration and broad adoption in fast-moving production environments (Ronde *et al.*, 2023). The time-independence and expertise requirements of simulation-based design thus present practical barriers to widespread use, particularly in small and medium-sized enterprises (SMEs) or multi-site deployments (Ronde *et al.*, 2023).

A related challenge concerns the static nature of many traditional approaches. Heuristics such as Systematic Layout Planning (SLP) and BlocPlan typically produce layouts under fixed assumptions about flows and relationships, with limited built-in capacity to adapt to evolving operations or to integrate streaming data from sensors and autonomous material-handling systems. Dynamic or zone-based planning efforts such as zone-based dynamic layouts and multi-objective extensions, highlight the need to incorporate changing conditions, uncertainty, and new objectives into layout decision-making; these avenues, while promising, remain less mature and often demand substantial domain-specific modelling effort (Tarigan *et al.*, 2019). The literature identifies a persistent gap between the agility demanded by modern smart factories and the relative rigidity of many traditional design methods (Herrmann *et al.*, 2022; Tarigan *et al.*, 2019).

Finally, the degree to which traditional methods accommodate uncertainty and disturbances is limited. Modern production systems are subject to demand volatility, machine breakdowns, and the integration of autonomous moving assets, all of which can invalidate a previously optimal or even feasible layout. Dynamic and multi-objective framing, including simulation-based and reinforcement learning-inspired planning, are increasingly advocated to address these disturbances; yet, such approaches are still emerging within practice (Tarigan *et al.*, 2019; Ronde *et al.*, 2023). The body of work also emphasizes that the adoption of new planning paradigms must contend with issues related to data availability, interoperability, and governance, underscoring structural barriers to replacing well-established heuristics with fully data-driven solutions (Herrmann *et al.*, 2022).

In sum, traditional factory layout design faces three interrelated challenges in the context of smart manufacturing: (i) limited scalability and high computational cost for large or high-dimensional problems when using exact optimization, (ii) limited adaptability and stativity in the face of dynamic disturbances and evolving flows, and (iii) constrained handling of uncertainty and real-time variability, which undermines responsiveness to demand fluctuations and equipment failures (Herrmann *et al.*, 2022; Putri and Dona, 2019; Tarigan *et al.*, 2019; Ronde *et al.*, 2023). These challenges motivate a shift toward learning-based and data-driven layout design approaches that can learn from historical and live data, adapt to changing conditions, and support multi-objective decision-making within digital-twin–enabled environments (Ono and Okpala, 2025). The literature thus paints a coherent picture: classical methods remain valuable for interpretability and tractable subproblems, but their limitations in dynamic, data-rich Industry 4.0 settings motivate integration with machine learning and related technologies (Herrmann *et al.*, 2022; Putri and Dona, 2019; Ronde *et al.*, 2023; Burggräf *et al.*, 2021).

Requirements in a Smart Factory Context

Smart factory layouts must be adaptable to frequent product changes, scalable to accommodate growing networks of processes, and capable of real-time decision-making to cope with volatility in demand and operations (Nwamekwe *et al.*, 2025g; Fuller *et al.*, 2020). This necessitates a modular, reconfigurable architecture for production lines and supporting equipment so that changeovers, line expansions, or fleet reallocations can occur with minimal downtime, a capability demonstrated by digital twin–driven and self-organizing shop-floor concepts Song *et al.*, 2023). Moreover, the integration of digital twins with automation technologies enables continuous validation and rapid iteration of layout configurations before any on-the-floor modification, aligning layout decisions with live performance data and future state projections (Nwamekwe *et al.*, 2025f; Pasupuleti, 2024).

The integration of digital twins, machine learning (ML), and reinforcement learning-based planning provides a holistic framework for addressing the complexity of smart factories. Digital twin-based planning supports end-to-end coordination of physical assets and their cyber representations, enabling concurrent optimization across multiple objectives such as throughput, energy efficiency, and system reliability while maintaining traceability and auditable decision rules (Nwamekwe *et al.*, 2025g; Pasupuleti, 2024). Additionally, ML-driven planning approaches offer scalable, data-driven automation for exploring and selecting layout alternatives in high-dimensional spaces, complementing traditional heuristics and allowing proactive reconfiguration in response to disturbances and shifting constraints (Wang *et al.*, 2024). Collectively, these capabilities support a unified system where digital twins, human-in-the-loop guidance, and automated decision support converge to deliver agile and resilient layout design in Industry 4.0 environments (Fuller *et al.*, 2020; Song *et al.*, 2023).

From an information management perspective, decision support systems in smart factories must fuse heterogeneous data streams from machine sensors to production schedules and market signals, to sustain up-to-date, context-aware layout configurations. Digital twins provide the computational foundation to ingest, synchronize, and simulate such data, enabling real-time validation and scenario testing without disrupting operations (Fuller *et al.*, 2020; Nwamekwe *et al.*, 2025e). Real-time optimization and predictive analytics, as demonstrated in digital twin-driven frameworks, empower continuous layout adaptation in response to detected anomalies or forecasted shifts in demand (Pasupuleti, 2024). Edge-enabled analytics and cross-domain data fusion further reinforce this capability by reducing latency and enhancing the system's responsiveness to both micro- (machine-level) and macro- (supply-chain) disturbances (Fuller *et al.*, 2020; Pasupuleti, 2024).

MACHINE LEARNING APPROACHES IN LAYOUT DESIGN

Supervised Learning Applications

Supervised learning models are increasingly employed to predict layout performance metrics such as throughput, cycle time, and energy consumption, enabling data-driven assessment of candidate configurations without running full-scale simulations for every option (Rummukainen *et al.*, 2020). Regression-style models map design features to expected key performance indicators (KPIs), providing quantitative estimates of how changes in layout influence performance (Rummukainen *et al.*, 2020). In parallel, classification-oriented approaches can be used to categorize layouts into efficiency classes based on predicted performance, supporting rapid screening of large design spaces. These supervised techniques serve as practical surrogates that accelerate decision-making by delivering actionable predictions without exhaustive simulation, as illustrated by surrogate-modelling efforts that approximate layout-related phenomena using data-driven mappings (Chen *et al.*, 2024). Collectively, these approaches demonstrate how learning from historical layouts and simulated results can yield scalable, explainable guidance for layout selection and incremental improvement (Rummukainen *et al.*, 2020).

The practical value of supervised learning in layout design is amplified when integrated with digital-twin ecosystems. Digital twins provide the data fabric and testbed that feed supervised models, enabling real-time validation and scenario testing across multiple objectives while maintaining auditable decisions (Nwamekwe *et al.*, 2025c; Fuller *et al.*, 2020; Song *et al.*, 2023; Pasupuleti, 2024). In this context, supervised models can be trained on both historical designs and digital twin-generated scenarios to predict outcomes for novel configurations and to rank alternatives efficiently, thereby supporting agile reconfiguration in Industry 4.0 environments (Nwamekwe *et al.*, 2025c; Song *et al.*, 2023; Rummukainen *et al.*, 2020). Surrogate modelling further extends this capability by substituting expensive physics-based evaluations with fast learned approximations, enabling rapid exploration of high-dimensional layout spaces and informing safer, data-driven iteration before any live changes are made (Chen *et al.*, 2024). These coordinated ML–DT approaches offer a practical pathway to scalable, transparent, and adaptive layout design in smart factories (Nwamekwe *et al.*, 2025b; Fuller *et al.*, 2020; Song *et al.*, 2023; Pasupuleti, 2024; Rummukainen *et al.*, 2020; Chen *et al.*, 2024).

Unsupervised Learning Applications

Unsupervised learning techniques are increasingly leveraged to reveal structure in factory data without labelled outcomes, enabling the grouping of machines or processes with similar operational characteristics to reduce inter-cell movement in cellular or modular layouts (Zhang *et al.*, 2022). Clustering-based approaches can identify natural groupings and adjacency patterns among equipment, workstations, and flows, supporting more compact and cohesive zone definitions that minimize travel distances and handling effort (Zhang *et al.*, 2022). In addition, hybrid dimensionality-reduction strategies that couple clustering with feature reduction help manage high-dimensional layout data, extracting meaningful representations that preserve critical relationships while reducing computational burden for subsequent layout analysis. Recent work also demonstrates that unsupervised, multi-agent–inspired learning can coordinate distributed layout decisions in digital-twin environments, enabling dynamic reconfiguration of assembly cells while maintaining coherence across the plant (Wang *et al.*, 2024). Collectively, these unsupervised learning approaches provide scalable, data-driven pathways to delineate functional spaces and guide initial layout choices in complex manufacturing networks. Unsupervised learning also offers powerful tools for monitoring layout performance through anomaly detection in sensor-rich factory environments. By learning compact representations of normal operations, unsupervised deep representations can detect deviations that signal bottlenecks or suboptimal arrangements, enabling pre-emptive interventions before disturbances cascade into performance losses. Empirical work across engineering domains shows that anomaly detection via clustering and dimensionality reduction can uncover unusual patterns in high-dimensional process data, informing layout adjustments and preventive maintenance strategies. Moreover, recent surveys highlight how unsupervised techniques including clustering and dimensionality reduction facilitate pattern discovery and outlier detection, underscoring their value for continuous improvement of factory layouts under uncertainty (Nwamekwe and Igbokwe, 2024). These capabilities collectively support proactive, data-driven layout optimization and real-time resilience in Industry 4.0 environments (Nwamekwe and Igbokwe, 2024).

Reinforcement Learning for Adaptive Layouts

Reinforcement learning (RL) has emerged as a powerful tool for dynamic and adaptive layout design, enabling agents to learn sequential layout decisions by interacting with a simulated or digital twin environment and receiving rewards tied to performance outcomes such as reduced travel distance or increased throughput (Zhao and Duan, 2024; Choi *et al.*, 2024; Heinbach *et al.*, 2025). This learning paradigm is particularly well suited to reconfigurable manufacturing systems where layouts must continuously adapt to fluctuating demands, disturbances, and evolving process structures (Choi *et al.*, 2024; Zhao and Duan, 2024). The body of work demonstrates RL-based approaches ranging from automatic facility layout design to deep RL for workshop layouts, often leveraging production-simulation environments to evaluate candidate configurations without costly live changes (Zhao and Duan, 2024; Choi *et al.*, 2024; Heinbach *et al.*, 2025). These advances are complemented by broader evidence that RL can bridge traditional facility layout problems with modern ML capabilities, highlighting RL's potential for scalable, generalizable, and data-driven adaptation in Industry 4.0 contexts (Burggräf *et al.*, 2021). Practical deployments frequently incorporate digital twin platforms to provide safe testing grounds and real-time feedback for policy improvement, reinforcing the viability of RL for adaptive layout challenges across diverse facilities and product mixes (Heinbach *et al.*, 2025; Akar and Turgay, 2023). Collectively, these studies underscore RL as a promising pathway to autonomous, resilient, and continuously optimizing layouts in smart factories, while also pointing to remaining challenges in transferability, data efficiency, and integration with live shop-floor systems (Burggräf *et al.*, 2021).

Hybrid AI Models and Metaheuristics

Hybrid AI approaches fuse ML models with metaheuristic optimization methods to tackle facility layout problems that are intractable for either paradigm alone (Peng *et al.*, 2018) In these hybrids, ML provides fast performance estimation, surrogate modelling, and data-driven insights into layout behaviour, while metaheuristics systematically explore large search spaces to escape local optima and improve robustness under uncertainty (Nwamekwe *et al.*, 2024b). This combination has been shown to enhance both solution quality and computational efficiency, enabling the optimization of complex layouts such as dynamic or stochastic environments where pure ML or classic heuristics may struggle (Peng *et al.*, 2018; Rummukainen *et al.*, 2020). Empirical work across manufacturing contexts demonstrates the value of hybrid AI for layout design. Metaheuristics coupled with soft computing or ML have been applied in shipyard and cellular manufacturing settings, yielding more robust and adaptable layouts than conventional methods alone (Nwamekwe *et al.*, 2024b). Hybrid frameworks that integrate GA-based search with stochastic or data-driven components have shown improved handling of variability and demand, supporting scalable optimization in dynamic facilities (Peng *et al.*, 2018; Wang *et al.*, 2024). The emergence of multi-agent cooperative swarm learning, often in conjunction with digital

Table 1: Method family to layout decision mapping.

Method family	Decision task	Inputs	Outputs	Primary performance indicators	Primary risks
Supervised	Predict KPI of candidate layouts	Layout features, historical KPIs, simulation outputs	Predicted throughput, cycle time, energy	RMSE/MAE, R^2, inference latency	Overfitting, poor transferability
Unsupervised	Zone formation / clustering	Sensor streams, flow matrices, adjacency data	Clusters, latent features, anomalies	Silhouette, DBI, stability index	Ambiguous clusters, interpretability limits
Reinforcement Learning	Sequential reconfiguration policy learning	Digital twin states, reward signals, actions	Policy, optimized action sequence	Cumulative reward, distance reduction %, throughput gain %	High compute cost, unstable training
Hybrid	Multi-objective global search with learning surrogates	All above + metaheuristic states	Pareto layouts, surrogate estimates	Hypervolume, convergence rate, robustness	Integration complexity, tuning overhead

twins, illustrates how distributed ML-augmented searches can coordinate complex reconfiguration tasks and accelerate convergence to high-quality layouts in Industry 4.0 environments (Wang *et al.*, 2024; Burggräf *et al.*, 2021).

Table 1 structurally contrasts learning paradigms by task, data requirements, outputs, metrics, and risks, enabling rapid method selection and clarifying trade-offs between predictive accuracy, adaptability, interpretability, and deployment complexity.

DATA AND DIGITAL INFRASTRUCTURE

Sources of Data for Layout Optimization

Machine learning-based layout optimization relies on rich and diverse datasets drawn from multiple sources, including IoT sensor streams, enterprise data, and simulation outputs. In practice, IoT sensor data provide real-time measurements that reflect the current state of production, such as machine utilization and energy consumption, which can feed timely diagnostics and enable rapid layout adaptation (Lind *et al.*, 2022; Nåfors and Johansson, 2021; Hovanec *et al.*, 2023). At the same time, ERP/MES logs contribute operational metrics like order processing times and resource allocation, supplying essential context for aligning layout decisions with production planning and execution, especially when integrated into digital-twin ecosystems (Lind *et al.*, 2022; Nåfors and Johansson, 2021). Beyond these live feeds, simulation outputs from digital twins and related simulation environments offer historical and hypothetical performance data that are invaluable for training, validating, and testing ML models prior to any live change (Eschemann *et al.*, 2024; Nwamekwe and Chikwendu, 2025a; Choi *et al.*, 2024).

The integration of these heterogeneous data streams requires robust data fusion, synchronization, and governance to realize a coherent data fabric for layout optimization. Digital twins and simulation platforms act as the orchestration layer, enabling seamless ingestion and alignment of sensor, enterprise, and simulation data for end-to-end decision support (Lind *et al.*, 2022; Nåfors and Johansson, 2021; Eschemann *et al.*, 2024; Choi *et al.*, 2024). By combining real-world and synthetic data, ML models can generalize better across layout variants and scenarios, supporting proactive, data-driven reconfiguration in Industry 4.0 environments. These data infrastructures and pipelines underpin scalable and transparent layout design practices, where ML augments traditional methods with continual learning and scenario-aware optimization (Ronde *et al.*, 2023).

Role of Digital Twins in Layout Learning

Digital twins serve as experimental platforms where layout configurations can be tested, validated, and optimized in virtual space before physical implementation, a role clearly demonstrated by studies that explicitly model up-to-date factory layouts using twin-enabled environments (Lind *et al.*, 2022; Nåfors and Johansson, 2021; Hovanec *et al.*, 2023). These works show that digital twins provide faithful representations of physical assets and processes, enabling scenario testing with realistic spatial relations and timing, which supports rapid validation of alternative layouts without disrupting production on the shop floor (Lind *et al.*, 2022; Hovanec *et al.*, 2023). Moreover, immersive and VR-enabled twin deployments illustrate how virtual spaces can accelerate iteration cycles and facilitate collaborative evaluation of layout options prior to any on-site changes (Hovanec *et al.*, 2023). Beyond testing, digital twins deliver real-time data streams that fuel continuous learning for ML-based layout optimization, enabling layouts to adapt as conditions evolve. The literature documents twin-enabled platforms that ingest sensor data, production logs, and digital-model feedback to drive ongoing reconfiguration and learning-driven decision support (Lind *et al.*, 2022; Choi *et al.*, 2024), while AI/ML models trained on both real and simulated twin data can generalize across layouts and scenarios to anticipate bottlenecks or demand shifts (Eschemann *et al.*, 2024; Nwamekwe and Chikwendu, 2025b). The integration of digital twins with production simulations and reinforcement-learning workflows further demonstrates how safe, data-driven experimentation within a twin environment can accelerate the design-learn-deploy cycle for adaptive layouts in Industry 4.0 contexts (Nwamekwe and Chikwendu, 2025b; Choi *et al.*, 2024; Ronde *et al.*, 2023).

Fig. 1 depicts an end-to-end closed loop where heterogeneous data feed the digital twin, models learn policies, optimization selects layouts, and deployment updates operations under governance, explainability, and security controls.

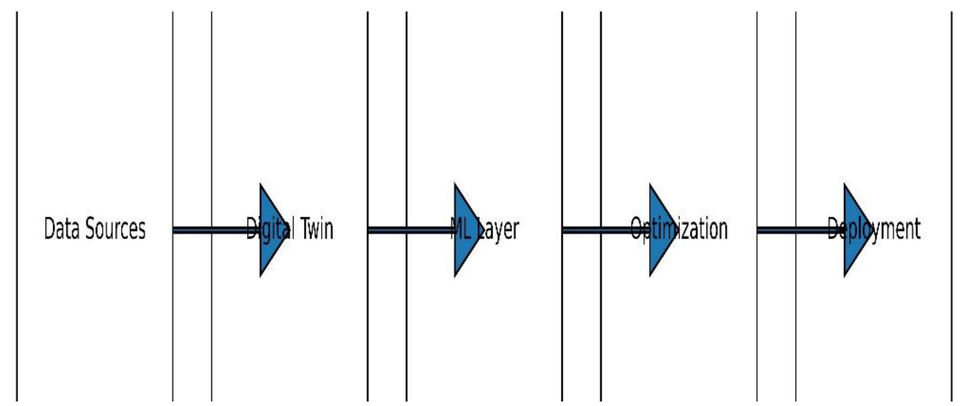

Fig. 1: Digital twin enabled layout learning pipeline.

Data Quality, Integration, and Real-Time Challenges

Despite the promise of data-driven layout optimization, practical deployment faces several data-centric hurdles, including incomplete datasets, inconsistent data formats across disparate sources, and latency in integrating real-time streams from sensors, Enterprise Resource Planning (ERP)/Manufacturing Execution Systems (MES), and simulation outputs (Fuller *et al.*, 2020; Göppert *et al.*, 2021). These issues hinder timely, reliable decision-making and can degrade the performance of ML models trained on fragmented or misaligned data, underscoring the need for robust data governance and cleansing practices in smart-factory contexts (Fuller *et al.*, 2020). Additionally, as real-time sharing becomes increasingly essential for agile reconfiguration, establishing standardized data-sharing protocols and interoperable data models emerges as a pressing priority for scalable deployment of digital-twin–assisted layout optimization (Göppert *et al.*, 2021; Pang *et al.*, 2021). To address these challenges, the development of ontology-based modelling and standardized deployment infrastructures is recommended to improve data interoperability across plant systems and digital twin (DT) platforms (Göppert *et al.*, 2021). The digital thread concept further emphasizes end-to-end data provenance, versioning, and traceability to support repeatable experimentation and auditable decisions in layout learning workflows (Pang *et al.*, 2021). Simultaneously, safeguarding data streams and DT architectures against security threats remains crucial, as evolving attack surfaces can compromise model reliability and trust in automated layout decisions (Nwamekwe and Nwabunwanne, 2025b). Together, these facets data quality, integrated pipelines, and secure, real-time data sharing constitute foundational prerequisites for effective ML-enabled layout learning in Industry 4.0 environments (Fuller *et al.*, 2020; Göppert *et al.*, 2021; Pang *et al.*, 2021; Nwamekwe and Nwabunwanne, 2025b).

COMPARATIVE REVIEW OF CASE STUDIES AND APPLICATIONS

Reported Benefits of ML in Factory Layout

Empirical evidence indicates that ML-enabled factory layouts can enhance operational efficiency by minimizing travel distances, material handling costs, and energy consumption. For instance, simulation-based deep reinforcement learning (DRL) methods have shown improvements in objective values related to material flow and space utilization, leading to reductions in travel distances and handling efforts across various layouts (Okpala *et al.*, 2024). ML-enabled surrogate modelling and data-driven layout optimization have also yielded measurable efficiency improvements in practice, with studies demonstrating significant gains in layout performance and expedited evaluation processes compared to traditional methods. These findings collectively underscore the potential for ML to reduce search efforts while improving layout quality in complex production environments (Lin and Jiang, 2023). In addition to single-location efficiency, ML methods enhance flexibility and enable rapid reconfiguration in response to changes in product mixes and supply-chain disruptions. Transferable multi-objective reinforcement learning frameworks suggest that learned policies can effectively generalize across different layouts and facility types, allowing quick adaptations to new line designs and demand profiles without necessitating a complete restart (Klar *et al.*, 2023). Supporting evidence from studies on process plants and facility layouts suggests that integrating ML with simulation and optimization can facilitate robust reconfiguration under uncertain conditions, thereby promoting continuous improvements as circumstances evolve (Lin and Jiang, 2023). Finally, the success of data-driven layout generation and optimization across diverse contexts from logistics node optimization to modular cell layouts highlights the broad applicability of ML-driven methods for maintaining agility in Industry 4.0 manufacturing networks (Rummukainen *et al.*, 2020).

The heatmap in Fig. 2 shows research concentration across objectives, with reinforcement and hybrid approaches

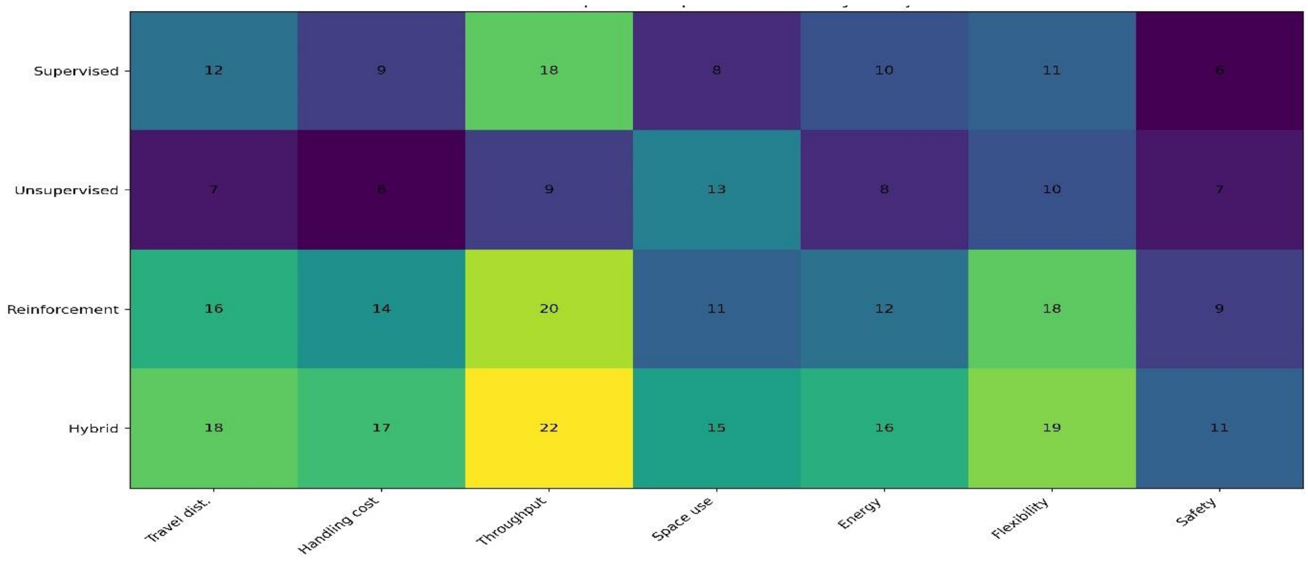

Fig. 2: Evidence map heatmap.

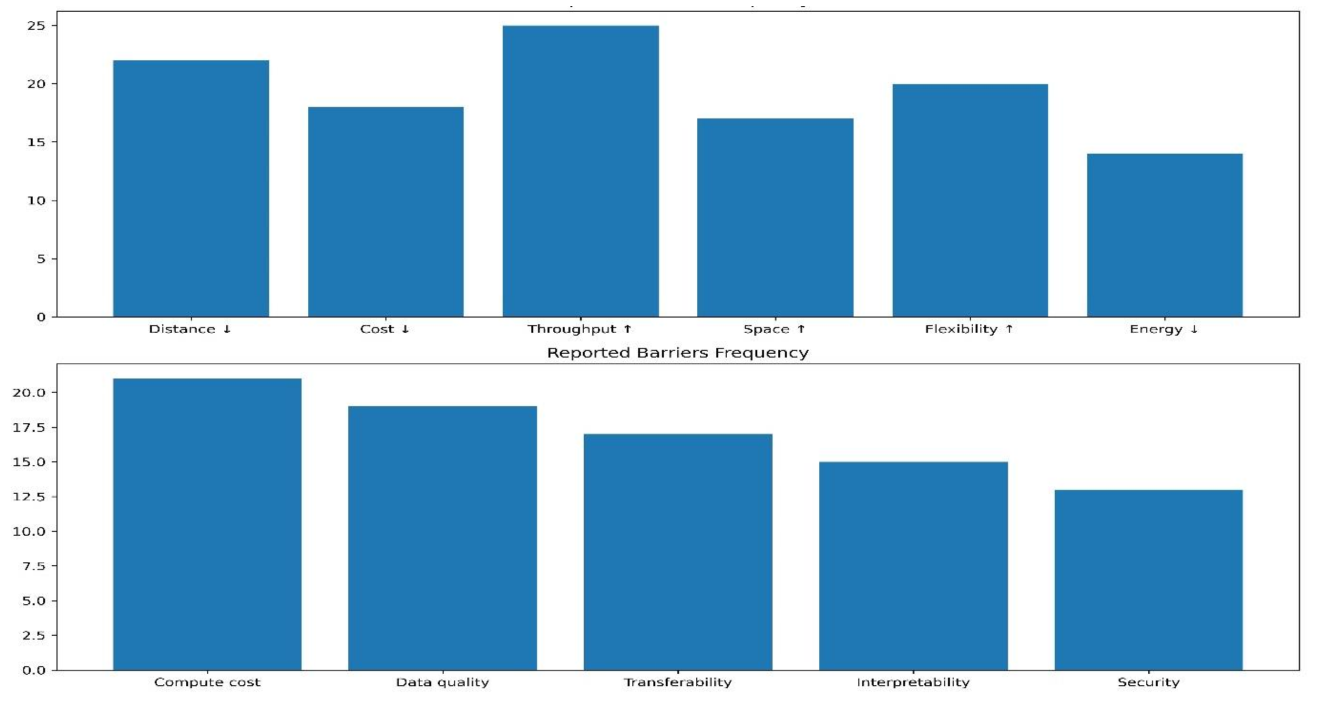

Fig. 3: Benefits versus limitations frequency bar chart.

dominating throughput, flexibility, and travel reduction, indicating stronger empirical support for adaptive, multi-objective optimization than static supervised or clustering methods.

Limitations in Current Implementations

Despite demonstrated potential, current ML-enabled factory layout implementations face several practical barriers. Notably, the training and evaluation of complex models, especially deep reinforcement learning (DRL) and discrete event simulation (DES)-assisted pipelines, can be computationally expensive and time-consuming, limiting their feasibility for rapid design cycles and iterative testing (Klar *et al.*, 2023). These computational demands are compounded when attempting to scale to large, high-dimensional layouts, where the search space grows combinatorially and training times escalate accordingly (Klar *et al.*, 2023). In addition, generalizability across industries remains a challenge: models trained on one set of facility characteristics or process flows often struggle to transfer effectively to different plants or product mixes, reducing their applicability in multi-site or cross-domain deployments (Burggräf *et al.*, 2021). The literature also highlights interpretability concerns, as many machine learning and deep learning approaches operate as black boxes, hindering transparent decision-making and complicating regulatory acceptance in safety- and compliance-sensitive environments (Burggräf *et al.*, 2021). These limitations help explain the slower adoption of ML-driven layout solutions in conservative or highly regulated manufacturing contexts. To address them, researchers advocate for transferable and multi-objective reinforcement learning frameworks, surrogate models, and hybrid approaches that can generalize better and offer more explainable guidance, along with standardization and governance to ease integration with existing systems (Klar *et al.*, 2023). The results emphasize the need for methods that deliver robust performance across varied facilities while enabling auditable and interpretable decision processes, which remains an active area of research for ML-assisted layout design in Industry 4.0 (Burggräf *et al.*, 2021).

Frequency comparison (Fig. 3) highlights dominant gains in throughput and travel reduction, while computational burden and data quality remain primary barriers, emphasizing that scalability and governance issues currently constrain industrial deployment.

Emerging Industrial Case Studies

Recent studies in the automotive and electronics sectors illustrate promising ML-driven layout applications, with reinforcement learning (RL) used to perform dynamic line balancing and to inform clustering techniques for modular cell design. In particular, RL-based balancing and sequencing have been demonstrated for mixed-model assembly lines, enabling more agile responses to product variety and demand fluctuations typical of automotive manufacturing. Complementary work shows RL can support dynamic scheduling in flow-shop settings, where agents learn policies that balance throughput, lead times, and resource utilization under changing conditions. These studies are frequently embedded in simulation or digital-twin environments, which provide safe testbeds for evaluating layout changes before physical implementation and help translate learned policies into actionable shop-floor decisions (Liu *et al.*, 2022). Beyond traditional manufacturing sectors, emerging evidence points to broader application horizons, including additive manufacturing (AM) facilities, where ML-driven layout optimization can enhance space utilization and material flow in complex, reconfigurable environments. The cross-domain nature of recent RL-based layout work exemplified by transferable multi-objective planning in simulations and by learning from prior designs across facilities, suggests that similar approaches may benefit AM contexts as well, even though AM-specific case studies are still developing (Liu *et al.*, 2022). This trend underscores ML's potential to generalize across industry types, supporting agile reconfiguration and multi-objective optimization in Industry 4.0, with AM representing a salient frontier for future empirical validation (Liu *et al.*, 2022).

OPEN CHALLENGES AND FUTURE DIRECTIONS

Scalability and Real-Time Adaptability

Future research must address the scalability of ML-based layout methods to large-scale factories and their capability to adapt layouts in real time without incurring prohibitive computational overhead. Recent work using simulation-based reinforcement learning (RL) for factory layouts demonstrates clear potential for dynamic optimization but also highlights scalability constraints as problem size and complexity grow (Klar *et al.*, 2023). Moreover, generalizability across different plants and product mixes remains a critical hurdle; studies on transferable RL for layout planning emphasize the need for policies that can adapt beyond a single facility model (Klar *et al.*, 2023). The real-time decision-making requirement is underscored by efforts that couple RL with digital twins to enable responsive, on-the-fly reconfiguration while maintaining safe testing environments, as well as by AI-driven throughput predictions in simulated layouts that support rapid scenario evaluations without disrupting production (Okorocha *et al.*, 2022). To advance toward scalable, real-time adaptable solutions, several avenues appear promising. Hybrid strategies that combine RL with surrogate models or discrete event simulation (DES)-based evaluation can reduce training and evaluation costs while preserving solution quality (Klar *et al.*, 2023). Federated learning offers a pathway to leverage cross-facility data without centralizing sensitive information, aiding scalability and robustness in multi-site deployments. Complementary work on ontology-based data interoperability and digital twin frameworks can strengthen data integration and governance, supporting real-time data sharing and auditable decisions in layout learning workflows (Godfrey *et al.*, 2024). Collectively, these directions point toward developing transferable, multi-objective RL approaches reinforced by twin-enabled experimentation and interoperable data infrastructures to achieve scalable, real-time adaptive layout design in Industry 4.0 contexts (Heinbach *et al.*, 2025; Klar *et al.*, 2023; Liu *et al.*, 2022; Eschemann *et al.*, 2024).

Human–AI Collaboration in Layout Design

AI should be viewed as an augmenting tool rather than a replacement, and future systems are likely to feature interactive interfaces where human planners and AI agents co-design layouts to leverage complementary strengths (Song *et al.*, 2023). Such collaboration enables rapid exploration of design options, multi-objective trade-offs, and pattern discovery from high-dimensional data, while human experts provide safety, governance, and domain-context understanding that guide the search process and constrain ethically acceptable decisions (Chidiebube *et al.*, 2025; Lin and Wang, 2019). This human–AI synergy is evident in domains like healthcare facility design, where AI-driven Building Information Modelling (BIM) workflows support space optimization that respects clinical workflows and safety considerations, illustrating how machine intelligence can augment, not supplant, professional judgment (Chidiebube *et al.*, 2025). Concurrently, human factors research underscores the need to preserve ergonomics, usability, and operational practicality in AI-assisted layouts, ensuring that proposed configurations remain implementable on real shop floors (Nwamekwe and Igbokwe, 2024). Realizing effective human–AI collaboration requires robust data infrastructures and safe testing environments. Digital twins provide the experimental platforms for co-design, enabling iterative validation and optimization of layouts in a virtual space before physical changes, which is essential for building trust in AI recommendations (Akar and Turgay, 2023). To sustain learning and reuse across facilities, standardized data interoperability and governance enforced via ontologies and digital thread concepts, are critical to enable seamless human–AI interaction and auditable decisions across heterogeneous systems (Göppert *et al.*, 2021). Security considerations for digital twin ecosystems are also paramount, as robust protections are needed to preserve data integrity and decision transparency in collaborative layout learning (Nwamekwe and Nwabunwanne, 2025a). Taken together, these directions point toward interactive, twin-enabled, and governance-backed collaboration between humans and AI as a core pillar of scalable, responsible layout design in Industry 4.0 (Akar and Turgay, 2023; Göppert *et al.*, 2021; Nwamekwe and Nwabunwanne, 2025a).

Explainable and Interpretable Machine Learning

To foster trust and adoption in ML-driven layout design, explainable AI (XAI) methods must clarify how layout decisions are made and provide interpretable justifications for recommended changes. In manufacturing contexts, SHAP and LIME offer model-agnostic and local explanations that reveal which features most influence proposed layouts, supporting transparent decision-making and easier regulatory alignment. Research illustrates that these explainability tools can facilitate the understanding of complex predictions for practitioners, reinforcing the notion that transparent AI is essential for the broader acceptance of ML-assisted layout design (Song *et al.*, 2023). Moreover, systematic evaluations of interpretability robustness, assessing fidelity, stability, and reliability across scenarios are critical to ensure trustworthy guidance in dynamic production environments (Chowdhury *et al.*, 2025). Realizing scalable, interpretable ML for layout learning also calls for thoughtful methodological choices and governance. Hybrid approaches that combine interpretable models with post-hoc explanations, alongside human-in-the-loop validation, can help reconcile performance with transparency and safety requirements (Chowdhury *et al.*, 2025). Cross-domain syntheses further suggest that domain-agnostic explainability frameworks and standardized evaluation metrics will be key to benchmarking explanations and building user trust in AI-generated layouts across industries (Song *et al.*, 2023). Collectively, these directions point toward explainable, auditable, and human-centered ML workflows as foundational to the responsible deployment of ML-driven layout optimization in Industry 4.0 settings (Chowdhury *et al.*, 2025).

Sustainability and Green Factory Layouts

Sustainability is increasingly prioritized in modern manufacturing, and machine learning (ML)-driven layout optimization offers a path to reduce energy consumption, minimize waste, and integrate renewable energy sources within factory networks (Zhang *et al.*, 2022; Sonta *et al.*, 2021). Empirical work demonstrates that data-driven and ML-assisted layouts can yield energy savings and emissions reductions across diverse settings, including energy-saving manufacturing workshops using multi-objective particle swarm optimization (PSO) (Zhang *et al.*, 2022), data-driven building layouts for energy efficiency (Sonta *et al.*, 2021), and energy-aware planning approaches for construction-site layouts that emphasize green performance (Wang *et al.*, 2024). Additional studies illustrate broader opportunities for ML to enhance sustainable outcomes through predictive optimization and IoT-enabled energy management in complex facilities (Anand *et al.*, 2024), with deep learning-driven energy system optimization further supporting greener design choices (Igbokwe *et al.*, 2025c). To advance sustainable ML-driven layouts, researchers should emphasize multi-objective formulations that explicitly balance productivity with energy use and environmental impact, including the integration of renewable sources and storage within layout decisions (Zhang *et al.*, 2022; Wang *et al.*, 2024). Opportunities also lie in applying ML to optimize energy grids and facility energy management, enabling layouts that can adapt to fluctuating renewable generation and demand (Igbokwe *et al.*, 2025a; Anand *et al.*, 2024). Collectively, these directions point toward green, energy-aware, and resource-efficient layouts enabled by ML, reinforced by data-driven validation and scalable optimization techniques across various industries (Zhang *et al.*, 2022; Sonta *et al.*, 2021; Wang *et al.*, 2024; Igbokwe *et al.*, 2025a; Anand *et al.*, 2024).

Integration with Next-Gen Technologies

The trajectory of ML-enabled factory layout design is increasingly likely to integrate quantum computing to accelerate optimization, enabling faster exploration of large combinatorial layout spaces through quantum-inspired learning and generation approaches. Foundational work on quantum ML, including variational generators, suggests potential speedups in generating and evaluating candidate layouts, which may transform near-real-time decision cycles in complex facilities (Romero and Aspuru-Guzik, 2020). Complementary research on quantum federated learning signals opportunities for collaborative optimization across distributed plants without sharing raw data, potentially enhancing cross-site consistency while preserving data privacy, albeit with added noise handling and calibration challenges (Chen *et al.*, 2024). Together, these strands point to a near-future ecosystem where quantum advantages augment classical ML for layout design, especially in multi-site, multi-objective settings (Romero and Aspuru-Guzik, 2020; Chen *et al.*, 2024).

Concurrently, federated learning (FL) and edge AI are poised to redefine how design knowledge is shared and acted upon on the shop floor. FL enables collaborative training across distributed factories without centralizing sensitive datasets, addressing privacy and governance concerns while enabling broader data-driven generalization; however, challenges such as non-IID data, communication overhead, and synchronization must be managed for industrial scale deployments (Emeka *et al.*, 2025). Edge AI further supports on-site, low-latency adaptation by pushing intelligence to the network edge, reducing latency for real-time layout updates and enabling responsive reconfiguration in dynamic environments; this is underpinned by work on intelligent edge computing and edge-cloud orchestration in digital twin-enabled factories (Okeagu *et al.*, 2024). The convergence of FL, edge AI, and quantum ML thus outlines a multi-layered future where privacy-preserving collaboration, real-time local inference, and quantum-accelerated optimization collectively enable scalable, adaptive, and verifiable layout learning in Industry 4.0 contexts (Emeka *et al.*, 2025; Okeagu *et al.*, 2024).

CONCLUSION

Evidence across the reviewed studies indicates that machine learning provides a practical route for layout design under Industry 4.0 requirements. Traditional approaches built on heuristics, mathematical programming, and simulation remain valuable for transparency and bounded problem instances, yet these approaches face persistent limits under large, dynamic, and data-rich factory settings. The reviewed literature consistently links these limits to growth in search space, changing product mix, autonomous material handling, and disturbance-driven variability, which reduce the effectiveness of static, one-shot layout decisions. Supervised learning supports rapid screening and surrogate prediction of layout performance metrics such as throughput, cycle time, and energy-related indicators, which reduces dependence on repeated full simulations for each design alternative. Unsupervised learning supports structure discovery in sensor and operational data, including clustering of machines and processes and anomaly detection, which improves zone formation, monitoring, and continuous improvement logic for evolving layouts. Reinforcement learning supports sequential, adaptive decision-making in simulated or digital twin environments through reward-driven policies tied to flow efficiency objectives, enabling reconfiguration under demand volatility and operational disturbances. Hybrid approaches that combine learning models with metaheuristics strengthen exploration of large combinatorial spaces and support multi-objective trade-offs, with digital twin platforms serving as the validation and experimentation layer that links learning to operational feasibility.

Reported benefits concentrate on reduced travel distance and material handling burden, improved space utilization, faster evaluation of alternatives, and increased flexibility through data-driven reconfiguration. Yet, current implementations still face barriers that limit scale-up. Computational burden remains high for deep reinforcement learning and simulation-assisted pipelines. Transfer across plants and product families remains inconsistent. Interpretability gaps limit trust and governance in layout decisions. Data quality, interoperability, latency, and security constraints across IoT, MES, ERP, and digital twin stacks further reduce deployment readiness. Sustainability objectives require explicit inclusion in layout objective functions rather than post-hoc assessment.

Future progress depends on five priorities aligned with the manuscript's open challenges. First, scalability and real-time adaptability through transferable policies, surrogate-assisted training, and edge-enabled inference to reduce latency. Second, human–AI collaboration through interactive co-design workflows in digital twin environments, with clear role boundaries and validated constraints for safety and practicality. Third, explainable and interpretable learning through auditable explanations, stable feature attributions, and standardized evaluation of explanation fidelity under scenario variation. Fourth, sustainability-oriented layout learning through multi-objective formulations that explicitly balance productivity with energy use, emissions, and waste. Fifth, integration with emerging technologies such as federated learning, edge intelligence, and quantum-oriented optimization concepts, supported by governance and interoperability standards for repeatable deployment across facilities.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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