PERFORMANCE MEASUREMENT IN LVHM MANUFACTURING: KPIS, TECHNOLOGIES, AND STARTUP GAPS

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Abstract

The high degree of product variability and the ever-changing demands of customers make performance monitoring a constant struggle in low-volume high-mix (LVHM) production settings. This research provides a systematic literature review in accordance with PRISMA principles, examining 42 peer-reviewed papers (2021–2025) sourced from Scopus and Web of Science. Research has indicated that lead time and makespan are the predominant performance indicators. Moreover, digital twins, reinforcement learning, and discrete-event simulation are being increasingly used to increase scheduling efficiency and cost effectiveness. A bibliometric study using R Studio indicates a significant focus on job shop scheduling and AI-driven optimisation. Critically, there is a substantial gap in the literature, as no study explicitly addresses startup LVHM manufacturing. This review lays the foundation for performance frameworks specifically designed for LVHM manufacturers in the early stages of development.

Keywords: Low-Volume High-Mix Manufacturing, Startup, Performance Metrics, KPI Framework.
JEL Codes: M11, L25, O33.

Introduction

In LVHM manufacturing applications, fluctuating customer demand and product variation pose significant efficiency challenges. These difficulties are not limited to the startup environment and affect prominent and well-established firms (e.g., small, niche manufacturers to large, globally operating corporations). Companies must continuously adapt their production systems and improve performance through data-driven decision-making to remain competitive (Gan et al., 2023). Therefore, performance measurement is essential for maintaining enhanced performance. Conventional financial measures such as ROI, productivity, and profit served as the primary performance indicators from the early 1900s until the 1980s. The second phase began in the late 1980s because of the worldwide changes. As foreign competitors offered more variety, lower prices, and higher-quality products, companies began to lose market share. Companies' strategic focus changed away from low-cost options to reclaim a competitive advantage. In addition to adopting modern production management practices, companies refocused on quality, adaptability, quick turnaround, and reliable delivery (Digalwar & Sangwan, 2011).

However, the most important question is whether traditional performance indicators can still be used and, if so, which indicators should be addressed when monitoring performance in this new era. In situations where many behaviors are

difficult to detect, some classic indicators may no longer be appropriate. Decision-making in companies that constantly change demand in an LVHM production environment is extremely difficult. Although mistakes cannot be tolerated under these conditions, negative consequences reach consumers immediately. However, the right and most cost-effective answers must be found in a complex network of interconnected options (Gunasekaran & Kobu, 2007).

The current industrial revolution, "Industry 4.0," is a product of recent advances in automation and manufacturing processes. It encompasses a wide range of topics, such as data management, manufacturing competitiveness, production methods, and efficiency (Pakeltiene & Ragauskaite, 2017). Some of the most important technologies that have led to the rise of fully automated and digital production settings are those that comprise Industry 4.0, such as cyber-physical systems, the Internet of Things, artificial intelligence, big data analytics, and digital twins (Jamwal et al., 2021). Recent studies reveal that LVHM industries have grown in recent years because of the integration of Industry 4.0 and the demand for product personalisation. Nevertheless, there are major gaps in domains such as real-time decision support, lean adaptation, and human–machine collaboration (Gan et al., 2023).

These challenges are particularly significant for young manufacturers. However, it is almost impossible for startups to assess performance and make real-time decisions because of constraints, including inconsistent information systems, limited resources, and insufficient standard operating procedures. They find it challenging to fully utilise the promise of digital transformation initiatives because of these limitations (Lindberg et al., 2015). This result is due to the complexity of industrial processes, the variety of inputs, and the interdependence of operations; the decision-making process becomes even more crucial (Gödri et al., 2019).

Therefore, the primary objective of this research was to identify contemporary key performance indicators (KPIs) and the technologies employed in performance management, decision-making, and planning processes inside the company. A variety of analyses have been conducted to provide further insights into the research. Additionally, several suggestions have been made to reduce the time spent on repetitive tasks, benefitting the scientific community. Furthermore, observations focus on the long-term viability of developing industries. In this context, this study examines three research questions.

Q1 - To identify the digital and operational performance metrics that are currently used in LVHM manufacturing.

Q2 – To identify technological tools (e.g., IoT, digital twins, ERP, dashboards) enabling data utilisation and decision-making in production.

Q3 – To identify gaps that exist in the current literature regarding performance metric frameworks for LVHM startups.

Methodology

This review followed the PRISMA 2020 methodology (Page et al., 2021), guided by the systematic-review guidance of Lame (2019). The Web of Science and Scopus databases were selected for their broad coverage of top-quality peer-reviewed publications. To ensure relevance to technology and industrial studies, the included targeted journal articles published between 1 January 2021 and 31 December 2025 in English were within the scope of Engineering. This period ensures that the latest trends and developments are covered and that the field limit aligns with the study topic of engineering-related performance and production systems, as mentioned in Table 1 below.

Table 1. Inclusion Criteria

| Inclusion Basis |
| --- |
| Journal Article |
| Timespan: 1st January 2021 to 31st December 2025 (Index Date) |
| English Language |
| Subject area - Engineering |

Search String

Scopus- (TITLE-ABS-KEY (("job shop" OR "make to order" OR "engineer to order" OR "high-mix low-volume" OR "low-volume high-mix" OR "high variety" OR "non repetitive") AND ("data-driven" OR "data analytics" OR "data utilisation*" OR "data collection" OR "data recording" OR "data capture" OR "data source" OR "KPI*" OR "key performance indicator*" OR "performance metric*" OR "performance measurement" OR "performance indicator*" OR "monitoring system" OR "dashboard"))) AND PUBYEAR>2020 AND PUBYEAR<2026 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (LANGUAGE, "English"))

Web of Science - (TS=("job shop" OR "make to order" OR "engineer to order" OR "high-mix low-volume" OR "low-volume high-mix" OR "high variety" OR "nonrepetitive") AND TS=("data-driven" OR "data analytics" OR "data utilisation*" OR "data collection" OR "data recording" OR "data capture" OR "data source" OR "KPI*" OR "key performance indicator*" OR "performance metric*" OR "performance measurement" OR "performance indicator*" OR "monitoring system" OR "dashboard")) AND PY=(2021-2025) AND DT=(Article) AND WC=(Engineering) AND LA=(English)

Literature screening and selection procedure

The papers included in this study underwent a methodical, multistage screening procedure to ensure their quality and relevance. The inclusion factors are listed in Table 1, and the additional exclusion criteria were used to filter documents in Microsoft Excel systematically. Evaluations of titles and abstracts were considered part of the screening process. In addition to the findings and conclusions, the overall quality assessment was determined by the clarity of the methodology, the presentation of the results, and the degree to which they aligned with the research aims. The selection process also considered the availability of full papers. An overview of the workflow is provided in Figure 1.
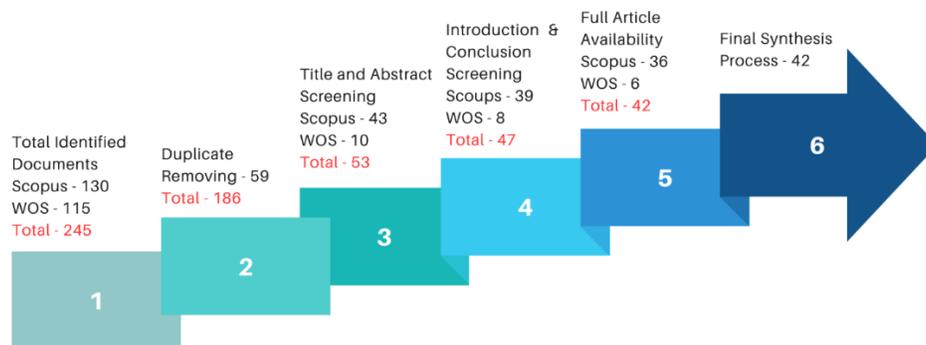
**Figure 1. PRISMA systematic screening methodology**

Results

Descriptive Results

Annual Scientific Publication Distribution

According to Figure 2, the majority of the 42 publications (36) were from Scopus, while a smaller percentage (6) were from Web of Science

(WOS). The year 2023 was the busiest for publications, with thirteen papers published, thirteen of which were included in the Scopus index. Compared with the eight publications in 2021 and 2025, 2022 and 2024 produced lower outputs, with 7 and 6 articles, respectively.
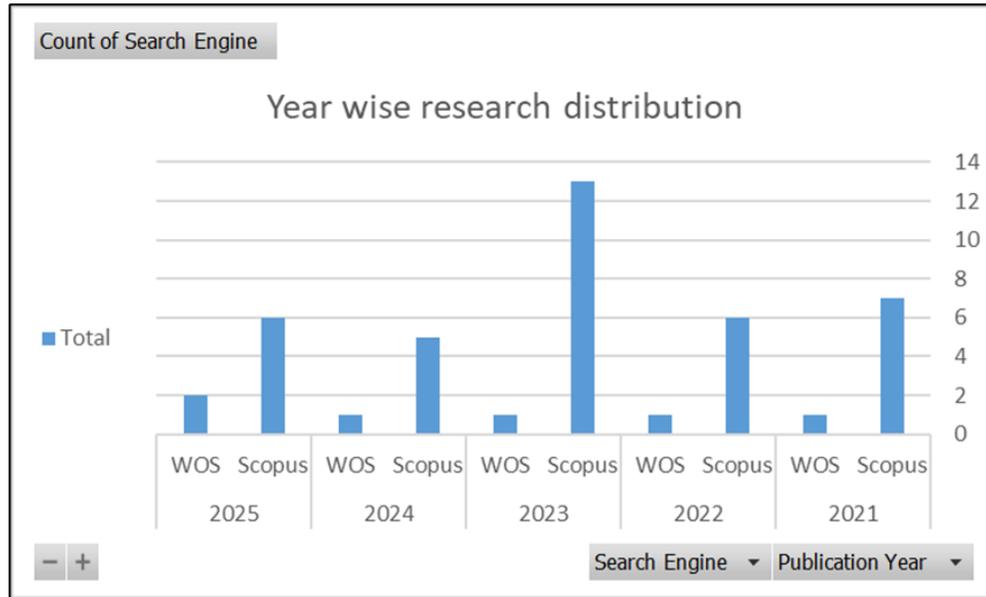

Figure 2. Publication Distribution

Most Frequently Used Key Performance Indicators

The investigation revealed considerable overlap in the performance indicators used across studies, with only 46 of the 96 KPIs distinct. Surprisingly, the studies examined did not consider

indicators such as raw material turnover rate. The most highlighted operational and digital performance KPIs are shown in Figure 3. The analysis shows a significant focus on KPIs such as lead time and makespan over other performance metrics.
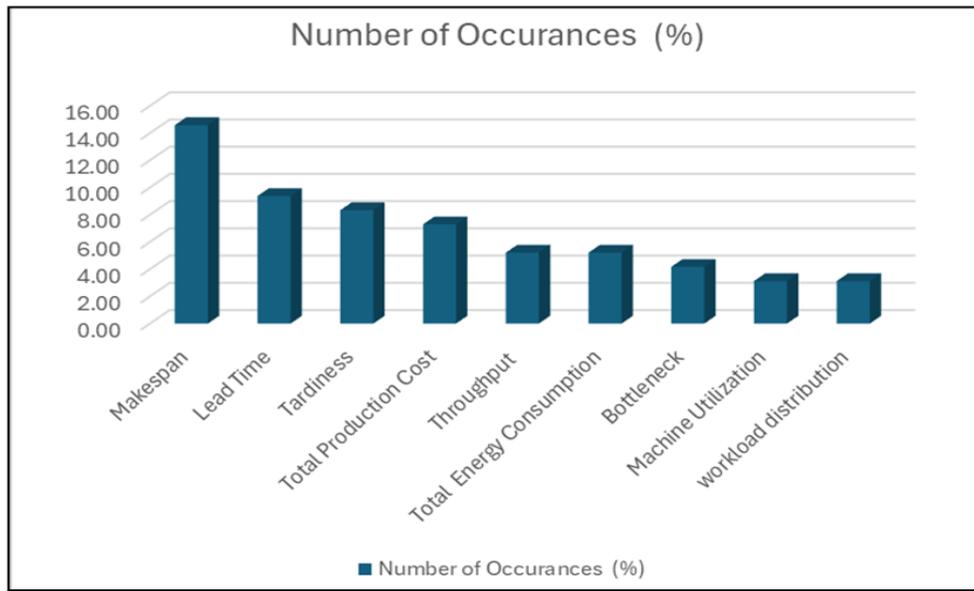
**Figure 3. Operational and Digital Performance KPI Indicators**

Co-Occurrence Analysis of Keywords

The bibliometric analysis produced a network of keyword cooccurrences (see Figure 4). The thickness of the edges indicates the strength of the co-occurrence of terms, and the size of the nodes indicates the frequency of the keywords. The clustering technique discerned four unique topics.

The blue cluster includes artificial intelligence and machine learning methods, such as reinforcement learning, deep reinforcement learning, and dispatching rules, indicating that RL-based approaches form the primary solution framework in the literature evaluated. The red cluster, which focuses on workshop and shop scheduling, confirms that the flexible job shop scheduling challenge is the primary field of study. The green cluster contains terms that are associated with Industry 4.0, such as digital twins, smart manufacturing, and dynamic scheduling. These terms reflect the growing incorporation of cyber-physical systems into scheduling research. The qualitative aspect of the field is represented by the purple cluster, which comprises terms related to performance, including performance metrics, optimal scheduling, and resource allocation.

The prominent correlations between job shop scheduling and reinforcement learning underscore how combinatorial scheduling and deep learning are currently at the center of attention in the field. There are unique opportunities for further research in the areas of energy efficiency, effective scheduling, and external factors affecting energy use, which have not been extensively studied.
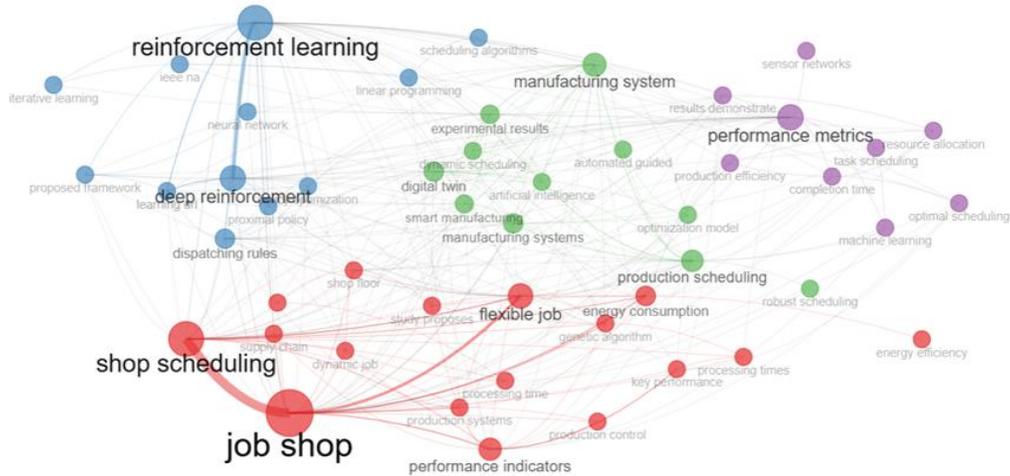
Figure 2. Cooccurrence Keyword Network Map (Abstract)

The authors categorised the solutions and classified them according to the evaluation criteria used. Data from the co-occurrence network analysis were used to create these groups. First, models employing artificial intelligence and machine learning (AI & ML), optimisation and metaheuristic algorithms (Optimisation), models grounded in simulation and digital twins (Sim & DT), and, finally, frameworks, tools, and hybrid systems (Framework) are used. Most studies on scheduling and production efficiency focus on optimisation, metaheuristic algorithms, and

simulations using digital twin models. This research clarifies the capacity and competence of this solution type in managing large datasets. AI and machine learning subsequently place greater emphasis on predictive modelling. Specifically, historical data are frequently noisy and unrefined. The emphasis on frameworks, tools, and hybrid systems is minimal. Table 2 summarises the 42 reviewed studies by source, analytical cluster, KPI or metric used, data method, reported performance outcome, and estimated applicability to LVHM startup contexts.

Keyword Plus Analysis of Scopus and WOS
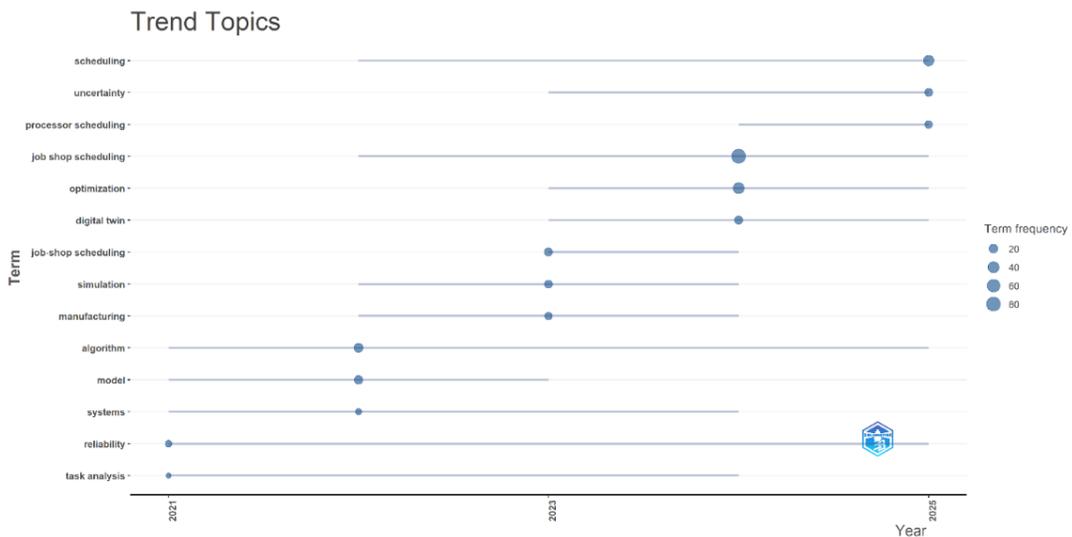
Figure 5. Keyword Plus Analysis of Scopus and WOS Search Engines (frequencies)

By utilising bibliometric trend analysis, Figure 5 systematically examines the upcoming trends in the LVHM manufacturing environment from 2021 to 2025. The field has undergone a clear transition. Early work centered on foundational topics, including reliability, algorithmic design, and systems modelling, before shifting toward applied simulation and manufacturing process

studies approximately 2022–2023. By 2024–2025, research converged on three dominant themes: job-shop scheduling optimisation, digital twin-enabled scheduling, and uncertainty management in processor scheduling. However, in previous years, specific areas such as production control and scheduling were more popular, suggesting that research interests are shifting.

Summarisation

Table 2. Summary of Operational Metrics

Source	Cluster	Metric/KPI used	Data Method	Performance Outcome	LVHM startup Applicability
(Aslan et al., 2023)	AI & ML	Lead Time, Prediction Accuracy	Sensor Data/hierarchical ensemble deep learning algorithm	Higher accuracy on synthetic data.	Low - Demands big historical datasets and deep learning architecture
(Jyothi & Dubey, 2023)	Optimisation	Nonprocessing energy consumption, Total weighted tardiness, and earliness, Makespan	Artificial Tree (FAT) and Atomic Orbital Search (AOS) - FAT-AOS method	Best makespan = 1370. Median makespan = 1720. Worst makespan = 2268.	Low - Needs expert metaheuristic configuration.
(Ding et al., 2025)	AI & ML	Makespan, Total Tardiness, Energy Consumption	Hierarchical Multi-Policy Soft Actor-Critic (HMPSAC) algorithm	No special findings were discussed.	Low - Large RL training data and GPU-level computing needed.
(Antons & Arlinghaus, 2022)	Sim & DT	Cost-minimal production	Multiagent based discrete-event simulation	Addresses process time variance and market fluctuations.	Medium – Idea can be transferable DES cyber-physical setup requires investment.
(Albayrak & Önüt, 2024)	Optimisation	Total energy consumption, Total machine workload, Makespan, and Reducing Scrap	NSGA II algorithm	The suggested approach outperforms several well-known multiobjective algorithms, including SPEA2, SMS-EMOA, and AGEMOEA2.	Low - A high level of expertise is needed for NSGA-II tuning..
(Li et al., 2022)	AI & ML	Makespan, Total energy consumption	Hybrid Deep Q Network (HDQN)	Outperformed the traditional method.	Low - Real-time sensor feeds and RL pipelines are not practical at startup.
(May et al., 2024a)	Sim & DT	Machine Utilisation, Throughput, Work in Process (WIP)	Automated simulation model generation (ASMG) framework	Reusable and flexible, the framework is constrained by the domain specificity and quality of the	Medium – Concept can be useful; an organised data structure is

				supplied data.	possible over time.
(Rohaninejad et al., 2023)	AI & ML	Production cost, Optimality, Scheduling efficiency	Monte Carlo simulation, Neural networks + K-means heuristic Satisfiability, Modulo Theories (SMT)	No special findings were discussed.	Low - Clean demand history and ML development capabilities needed.
(Lee & Yang, 2023)	Sim & DT	Production Throughput, Computation Overhead	Multiagent simulation with DT.	Statistical metamodelling reduces simulation cost while maintaining accuracy.	Low – depend on process maturity and simulation infrastructure.
(Li & Chen, 2023)	Sim & DT	Makespan, Total Carbon Emissions, Total Production Cost, Product Quality Stability	Dynamic scheduling strategy of the digital twin-driven MPFJSP	No special findings were discussed.	Low - Need robust processing data and cyber-physical integration.
(Xue et al., 2022)	AI & ML	Bottleneck Index	Autoregressive moving average (ARMA) model	The simulation model uses the bottleneck index to precisely identify bottlenecks, which is confirmed using actual remanufacturing data.	Low – Requires continuous time-series sensor data.
(Bao et al., 2023)	Optimisation	Number of overdue jobs, Total overdue time, Job completion time, Comprehensive load rate, Maximum load rate of machine tools	Genetic algorithm	Reducing task completion time and increasing diversity are achieved by increasing population size and the number of iterations.	Low – need process parameters and depth of technical expertise.
(Miqueo et al., 2023)	Sim & DT	Productivity (units/operator-hour), Lead Time (min), Milkrun Utilisation (%), Assembly Line Stock (units)	Discrete events simulation model	Component stock and milkrun usage are increased by multimodel lines (+24% and 22%, respectively).	Medium – process can be transferable.
(Brochado et al., 2023)	AI & ML	Bottleneck	Graph-based representations (QDG)	To identify and anticipate bottlenecks, little information is needed, and the accuracy of bottleneck prediction exceeds 90%.	Medium – Low data usage makes it more accessible than most ML methods.
(Chen et al., 2025)	AI & ML	Product completion time	Explainable multilayer heterogeneous graph attention network (M-HGAT)	Compared with the top-performing benchmark model, the suggested M-HGAT model reduces RMSE by 48%.	Low - Need aircraft assembly scale and domain data.
(Liang et al., 2023)	Optimisation	Makespan	Adaptive GA with new neighbourhood structure	No special findings were discussed.	Low computational competence and technical

					expertise are needed for adaptive GA.
(Patil et al., 2024)	Framework	Lead Time	MS Excel and Power BI	Enhanced decision-making through visibility and analytics	High – Low cost, directly usable.
(Mousavipour et al., 2022)	Optimisation	Makespan, Maximum Tardiness	A novel Bi-Objective MILP model	No special findings were discussed.	Low - demands considerable operations research knowledge.
(Gödri, 2022)	Framework	Delivery Precision, Lead Time, Resource Utilisation	Generic decision support workflow	No special findings were discussed.	High - adaptable to low-resource settings.
(Kusrini & Miranda, 2021)	Framework	Reliability, Responsiveness, Cost, Asset management, efficiency	SCOR version 12 business process framework	No special findings were discussed.	High - SCOR works regardless of firm size and tool.
(Ling et al., 2024)	AI & ML	Arrival Time Difference	PL trajectory analysis and optimisation using Manufacturing Task Data Chain (MTDC)	MTDC enables the integration of logistics and manufacturing data.	Low - Startups lack an integrated logistics and production data infrastructure.
(Aljinović et al., 2022)	Framework	Throughput, Scheduling efficiency, Cost-efficiency	-	Personalisation in technological choices is crucial. User preferences have a significant impact.	Medium – can be applicable depending on the budget.
(Filho et al., 2023)	Framework	Average delay, Percentage of late orders	Simplified Buffer-Rope (S-DBR) system	Most efficient when there are a lot of variation and a heavy load.	High - S-DBR works best in high-variability. No software needed.
(Wang et al., 2023)	AI & ML	Makespan, Total tardiness	Online due date prediction model using XGBoost	Compared to the TWK rule, XGBoost-based due date prediction decreased the makespan by 1.6% and overall tardiness by 65.0%.	Low - requires simulated training and historical completion records.
(Tarek et al., 2025)	Sim & DT	Total energy consumption, Makespan	DT framework with GA + GWO	No special findings were discussed.	Low - DT requires semantic modelling and mature data systems.
(Sit & Lee, 2023)	Sim & DT	Average order processing time, Average order-to-delivery, Average waiting time for production orders	Digital Twin Production Optimisation System (DTPOS)	The average order processing time was reduced by 52.63%, from 19 to 9.59 days. On-time completion with an average order-to-delivery time of 19.47 days	Medium - DT setup for LVHM requires investment but has high scheduling ROI.

(Ghaleb et al., 2021)	Optimisation	Cost savings (%), Rescheduling time impact	Modified hybrid genetic algorithm, an integrated proactive-reactive optimisation model	Compared to existing approaches, the proposed solution generated an average cost savings of approximately 27%.	Low - Requires condition-monitoring sensors and machine deterioration models.
(Liu et al., 2023)	Framework	Work in Process (WIP)	Machinery-oriented capacity adjustment approach via a reconfigurable machine tool (RMT)	Efficient at balancing capacity and preventing bottlenecks.	Medium – can be transferable, direct deployment is difficult.
(Wang et al., 2025)	AI & ML	Makespan, Machine utilisation	End-to-end DRL scheduler for the FJSPT	No special findings were discussed.	Low - Requires significant training and simulation.
(Hammedi et al., 2025)	Framework	Resource allocation, Lead time	The suggested architecture combines technology, lean concepts, and data-driven insights.	No special findings were discussed.	Medium – fit for startup requirements.
(May et al., 2024b)	AI & ML	Scrap rate, Quality-based yield	Artificial intelligence-based production control approach	No special findings were discussed.	Low – not a universal approach.
(Lee et al., 2025)	Framework	Bottleneck identification, Workload distribution	Manufacturing process analysis framework	No special findings were discussed.	Medium – Applicable for any industry type.
(Zhang et al., 2021)	AI & ML	Makespan, Total flow time, Tardiness	Closed-loop scheduling framework	No special findings were discussed.	Low - Requires structured shop floor sensor data.
(Zhou et al., 2021)	AI & ML	Makespan (RD), Machine utilisation (RU), Workload distribution (RV)	Reinforcement learning-based AI scheduler	Effectively managed uncertainty and unexpected events.	Low – high expertise needed.
(Zheng et al., 2021)	Optimisation	Uncertainty of process setup time, processing time	Particle swarm optimisation (PSO) algorithm	The suggested approach enhances scheduling performance and robustness.	Low – Requires uncertainty quantification.
(Karimi et al., 2021)	Optimisation	Production time, Transportation cost	NSCSA algorithm	No special findings were discussed.	Low - Extensive computing power and knowledge needed.
(Danishvar et al., 2021)	AI & ML	Energy consumption per unit, Operations cost, Makespan.	Fully connected deep neural network (FCDNN)	No special findings were discussed.	Low – Large training dataset and complex infrastructure.
(Yang et al., 2025)	Sim & DT	Flow time, Throughput	TPDR-based heuristics for order dispatching	Leading to a significant decrease in flow time of 22.03% and 45.71% for the average and maximum.	Medium – Simulation required more time and training.
(Yuan et al.,	AI & ML	Completion time	Completion time	Completion time	Low – technical

2023)		prediction accuracy	prediction model	prediction accuracy (>90%)	knowledge and continuous sensor streams needed.
(Zhang et al., 2024)	AI & ML	Weighted tardiness	Simulation-based numerical experiments	No special findings were discussed.	Low – High computational power and expertise needed.
(Heo et al., 2025)	AI & ML	Total Tardiness, Total Manufacturing Cost	Trained reinforcement learning agent	The suggested PPO-based approach reduces overall costs by 31.69%. ETD enhances performance by 27.74%.	Low - Needs structured job data and training.
(Kouider & Ait Haddadéne, 2021)	Optimisation	Minimisation of the makespan, Total completion time	Branch-and-bound and ε-constraint algorithms	No special findings were discussed.	Low - Heavy computing and OR skills needed.

Discussion

Operational and Digital Performance Metrics in LVHM (Q1)

In the context of LVHM, an assessment of 42 papers that have undergone extensive review reveals a distinct and consistent emphasis on time-oriented operational indicators. Lead time and makespan were the most frequently reported KPIs across the analysed studies, reflecting the industry's overall emphasis on delivery speed and production efficiency as key advantages. The following phase, which examined commonly observed indicators such as throughput, tardiness, machine usage, and work-in-process (WIP), demonstrated the importance of flow-based performance monitoring for scheduling LVHM production.

Three main types of KPIs emerge from the characteristics of the research evaluated. KPIs for time efficiency, including lead time, makespan, tardiness, and flowtime, have been reported in most studies and are now a focus of measurement in LVHM research. Concerns about operational capacity management are evident in the decreased frequency of resource utilisation KPIs, such as machine usage, work in progress, and task allocation. Although energy consumption, the scrap rate, and production cost are important strategic factors for long-term competitiveness,

they were included in only a few studies that focused on cost and quality KPIs. However, most studies' main goal is to improve scheduling, and this focus on time-dependent measures limits the view of operational performance (Simelyte et al., 2025). It ignores financial sustainability and quality factors that are just as crucial to production success.

The analysis included 46 separate measures, suggesting that several studies track similar data under different terminologies without attempts to amalgamate or consolidate them. The lack of standardisation makes it difficult to compare studies and limits the design of unified performance frameworks for LVHM conditions. According to the studies investigated in depth, there were no separate KPIs for performance indicators such as data quality, system responsiveness, or decision-making speed, suggesting that industries still lack digital performance metrics. However, there is a significant disparity between the operational and digital components of performance monitoring, which is especially critical given that production environments increasingly rely on real-time data infrastructure to support scheduling and management.

Technologies Enabling KPI Data Utilisation and Decision-Making (Q2)

Based on the classification presented in Table 2, four main technological and methodological clusters can be distinguished: artificial intelligence and machine learning, optimisation and metaheuristic techniques, simulation and digital twin methodologies, and framework or hybrid-system approaches.

The examined data show that technology serves two purposes in LVHM performance management. A framework for monitoring and addressing KPIs, along with the data required to build them, is provided. It generates KPI data and serves as the foundation for their reporting. However, the characteristics of this technology are variable in terms of accessibility and practical applicability for performance evaluation.

Among all the research projects, 17 (40.5%) address artificial intelligence and machine learning. These techniques mostly serve as optimisation engines rather than KPI monitoring tools.

Instead of being used as a statistic for management dashboards, the KPI serves as the optimisation objective, utilizing deep neural networks or reinforcement learning to minimize makespan or tardiness. While effective in controlled settings, they require specialized expertise, classifying them as performance optimisation tools rather than accessible measurement frameworks.

As detailed in Table 2, the optimisation and metaheuristic cluster accounts for 9 publications (21.4%). Methods like NSGA-II are used to concurrently optimise metrics such as makespan, energy consumption, and tardiness. Using a hybrid genetic algorithm, Ghaleb et al. (2021) reported cost reductions of 27%. However, their practical use for real-time monitoring remains constrained due to the extensive parameter adjustment and specialized knowledge required.

The simulation and digital twin methodologies, featured in 8 studies (19.0% of the total), represent a classification that is more pertinent to decision-making informed by key performance indicators. Sit and Lee (2023) demonstrate that the DTPOS framework

effectively connects real-time shop-floor data to tangible KPI outputs. This approach reduces the time spent processing orders by 52.63% and improves scheduling accessibility. There is a strong link between the data infrastructure and KPI tracking, which fits well with Q2's focus on solutions that make it easier to use data and make decisions. Similarly, discrete-event simulation approaches provide managers with real-world decision support beyond algorithmic optimisation, enabling them to analyse scheduling options and the consequences for KPIs before implementation.

The most relevant category for useful KPI monitoring is the framework and hybrid system approaches, with 8 studies (19.0%). In this group, Patil et al. (2024) show that a comprehensive scheduling solution using Excel and power BI improved lead-time monitoring and enhanced accessibility in production decision-making, eliminating the need for data scientists or technical experts. This study illustrates that carefully defined and monitored performance indicators enable the use of accessible, cost-effective solutions for efficient KPI monitoring and data-driven decision-making. The transition deviating from practical frameworks toward more intricate computational methods overlooks the potential to enhance performance measurement practices in resource-limited manufacturing contexts.

Gaps in the Literature for Startup LVHM KPI Frameworks (Q3)

The startup applicability assessment in Table 2 further confirms this gap by showing that only a limited number of studies are directly applicable to resource-constrained startup contexts.

The most prominent result from this review is the lack of literature focused on KPI frameworks for startup LVHM production systems. Every study in the examined sample addressed performance evaluation in developed, operationally established contexts with built-in data facilities, well-structured process documentation, and already adopted performance measurement methodology. The development, implementation, and monitoring of development-stage business environments and appropriate key performance indicators have not been prioritised in

any studies. Additionally, there is limited understanding of how manufacturers manage in the absence of satisfactory standard operating procedures, dependable data collection methods, or performance limitations in the early phase of the business.

This gap is further exacerbated because the performance-measurement limitations faced by established LVHM manufacturers differ substantially from those faced by start-up LVHM manufacturers. In addition to significant unknowns, limited finances, and often shifting operational goals, start-ups are obligated to build key performance indicator systems from the start. This investigation demonstrates that key performance indicators often examined include optimisation of makespan, machine utilisation rates, and energy consumption per unit. However, these KPI utilisation figures reveal that the process is reliable and that data are available to set these performance measures, which are two things startups usually do not have.

The results of the startup relevance analysis across all 42 studies provide objective validation of this claim. Rather than developing intricate optimisation algorithms that produce key performance indicators as a secondary result, four papers (9.5%) provided solutions that startup manufacturers could implement directly without specialised equipment. Researchers subsequently selected accessible monitoring techniques for tracking purposes. Ten research studies (23.8%) demonstrated considerable adaptation. In contrast, 28 trials (66.7% of the total) used approaches that were not compatible with the initially available resource-constrained environments.

However, research should focus on determining optimal methodologies for developing KPI frameworks. These models must begin with a limited array of essential indicators that can be quantified using basic instruments and thereafter evolve as the data infrastructure advances. Patil et al. (2024) demonstrated the utility of accessible tools, including Power BI and Microsoft Excel, in production process settings, thereby establishing a robust foundation. This research primarily aims to bridge the gap between the practical realities of

initiating LVHM manufacturing, performance indicators, monitoring systems, and performance optimisation.

Conclusion

The low-volume, high-mix production context is expanding rapidly. However, focused research areas do not adequately reflect this rapid expansion. This study identified a consistent trend across 42 investigations of LVHM industrial performance measurement, focusing on scheduling optimisation in conventional factory environments. In contrast, early-stage enterprises and digital performance measurement were notably overlooked.

The literature review reveals important trends during the analysed period. Lead time and makespan are the most common KPIs used in LVHM research, although financial, quality, and digital performance metrics are rarely considered. This result explains that operational performance in an LVHM context is not comprehensively understood in the literature. The conclusion is that extraordinarily complex proposed solutions are less beneficial to an organisation with constrained resources. Only four studies offered straightforward, framework-based methodologies that do not require any specific skills or resources.

While the review demonstrates a primary emphasis on time-oriented indicators, Table 2 highlights that research also utilizes related metrics such as prediction accuracy, computation overhead, and completion-time prediction accuracy to assess system performance.

Digital KPIs, such as data quality, decision speed, and system responsiveness, are not included as metrics in all 42 studies examined, despite their evident importance for companies operating in Industry 4.0 environments.

Researchers should prioritise the following tendencies: (1) Developing frameworks for KPIs utilising digital performance metrics; (2) Formulating measurement models tailored for early-stage firms; and (3)

Standardising KPI classification to ensure consistency across studies. Industry professionals must recognise that new enterprises should not

defer performance evaluations in anticipation of superior tools. Research indicates that using readily available tools such as Excel and Power BI to systematically focus on KPIs results in noticeable operational improvements and paves the way for the adoption of more advanced solutions in the future. A more sophisticated scheduling method is not necessary in this sector for substantial improvement. Straightforward and effective key performance indicators, frameworks, and systems can assist manufacturers from the inception of their operations. Additionally, high investments, advanced software, or extensive datasets are not necessarily needed for implementation. This research shows that there is currently no equivalent framework, and developing a logical representation is the most obvious next stage for LVHM manufacturing research and practices.

Several limitations should be considered when assessing the results of this review. Only the Scopus and Web of Science databases were used for the process examined. The ratings' relevance for startups in this review is derived from the authors' subjective interpretation rather than empirical evidence from startup contexts because of the lack of research specifically examining LVHM development in startup contexts.

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