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How information systems can support labor flexibility implementation: enhanced information architecture framework for industry 5.0

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Abstract

In Industry 5.0, where human-centricity, resilience, and customization are prioritized, implementing labor flexibility (LF) poses a persistent challenge, especially for make-to-order (MTO) systems. Although the benefits of LF are conceptually understood, effective frameworks for its practical deployment, particularly in data-scarce and digitally diverse environments, remain insufficient. This study addresses this gap by (i) employing discrete-event simulation (DES) to determine optimal thresholds for labor relocation and evaluate performance trade-offs, and (ii) proposing FlexiFlow, a structured information architecture framework designed to support LF implementation across different levels of digital maturity. The simulation identifies relocation logic and training setups that significantly reduce lead time while minimizing unnecessary labor movements. FlexiFlow complements this by guiding manufacturers, particularly small enterprises, in collecting and managing essential operational data for LF without necessitating full manufacturing execution systems (MESs) integration. Together, the results and framework provide actionable strategies that align with Industry 5.0's vision for adaptive, efficient, and human-centered production systems.

Keywords Labor flexibility · Information architecture framework · Operational data management · Manufacturing · Simulation

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1 Introduction

The emergence of Industry 5.0 (I5.0) marks a strategic shift from the technology-driven principles of Industry 4.0 to a more human-centric, resilient, and sustainable industrial paradigm (Grosse et al. 2023; Dacre et al. 2024; Ghobakhloo et al. 2024). Central to this transition is the strategic role of labor flexibility (LF). LF is defined as the ability of laborers to adapt their roles, skills, and schedules to meet changing operational demands. It encompasses several dimensions: real-time adaptability, role resourcefulness, and flexible employment structures. Together, these dimensions enable organizations to create agile, efficient, and inclusive production environments (Aleca and Mihai 2025; Wang et al. 2025b). Since humans remain the most adaptable and creative element in production systems (Hu and He 2020), LF is increasingly recognized as an essential enabler of dynamic workforce planning, resilience, and long-term industrial competitiveness (Grosse et al. 2023; Sarkar et al. 2025).

Despite its importance, the practical implementation of LF remains underexplored, particularly concerning real-time workforce management, organizational inertia, and data infrastructure challenges (Usman and Lu 2024; Ahmadi et al. 2025). Although theoretical models have proliferated, many overlook real-world constraints such as labor reallocation costs, labor fatigue, and the challenges small enterprises encounter in acquiring and managing the necessary data for LF at scale (Costa et al. 2023a; Ahmadi et al. 2024; Mejía-Moncayo et al. 2024). For instance, real-time LF requires synchronized access to operational data, including production queues, staffing levels, skill matrices, and shift constraints. However, many firms, especially small enterprises, lack the required digital maturity (Huang 2017; Tliba et al. 2023; Wang et al. 2025a). This issue is exacerbated by the fragmented integration of manufacturing execution systems (MESs), enterprise resource planning (ERP), and other digital tools, which hinders coordinated decision-making.

Furthermore, although studies have begun to explore advanced methods, including mixed-integer programming, discrete-event simulation (DES), and AI-driven scheduling to model LF impacts (Gong et al. 2021; Yan et al. 2022; Cimino et al. 2025), cross-sectoral validation remains limited. Most practical evidence focuses on the manufacturing sector, with sectors such as hospitality, construction, and healthcare underrepresented (Cirillo et al. 2023; Pandey et al. 2025). A recent paper by Ahmadi et al. (2025) identified five key LF strategies: real-time and adaptive management, skill and role development, dynamic employment practices, strategic workforce planning, and technological integration, mapping their adoption across industry sectors. While manufacturing research dominates due to its structured workflows and operational complexity, broader generalization is necessary to inform inclusive I5.0 policy and practice.

Real-time and adaptive LF strategies have demonstrated promising results in enhancing scheduling efficiency, reducing idle times, and optimizing workforce allocation (Dimény and Koltai 2022; Barkokebas et al. 2023). Similarly, approaches to skill and role development, such as ergonomic job rotation, multi-skilling, and cross-training, have been associated with productivity gains and improved human-centric adaptability (Henao et al. 2023; Schoenfelder et al. 2025). Despite these benefits, managing multi-skilled employees, overcoming resistance to change, and addressing limited training resources remain significant barriers (Chauhan 2016; Kaur et al. 2017). Furthermore, implementing these strategies often involves a trade-off: although LF strategies enhance responsiveness and reduce lead times, they can incur hidden costs related to transition fatigue, productivity dips, and training overheads (Costa et al. 2019; Porto et al. 2022). Addressing these challenges calls for structured, data-driven approaches that align digital technologies with human-centric values.

This study aims for a two-fold outcome. First, the authors employ DES to investigate how varying levels of LF impact performance measures, specifically lead times, idle times, and workforce allocation, in a stylized flow shop setting. This approach facilitates exploration of the trade-off between labor relocations and system efficiency, thereby contributing to the theoretical understanding of LF's operational dynamics. Second, the authors introduce a novel framework, FlexiFlow, which supports the structured implementation of LF by identifying relevant data sources, metrics, and integration points within current enterprise systems. FlexiFlow is particularly designed to assist small enterprises in navigating the complexities of LF implementation by providing an information architecture framework aligned with I5.0 goals.

This paper makes several contributions in theoretical, practical, literary, and methodological realms, each discussed below. Theoretically, it enhances the conceptual understanding of LF as a multidimensional strategy essential for human-centric manufacturing, elucidating its connections to resilience, adaptability, and sustainability in I5.0. Practically, it offers a simulation-based assessment of LF trade-offs and provides a practical framework to facilitate data collection, integration, and decision-making for real-world LF implementation. From a literature perspective, it builds on and extends recent systematic literature review findings (Ahmadi et al. 2025), bridging existing theoretical insights with practical challenges across different sectors. Overall, it is among the first to integrate performance-oriented simulation with an information architecture framework designed for dynamic LF, presenting a comprehensive view of implementation and evaluation within the I5.0 context.

The rest of this paper is structured as follows: Sect. 2 provides a review of the theoretical background of LF. Section 3 outlines the methodology, including the use of the simulation model (3.1) and the framework for LF implementation (3.2). Section 4 presents the results, highlighting the impact of LF on performance improvement (4.1) and demonstrating LF's practical applicability using the new framework (4.2). Section 5 discusses the key findings, and Sect. 6 offers conclusions.

2 Related work and conceptual framing

This section offers the essential theoretical background, detailing LF in Sect. 2.1, exploring its practical applicability, especially within the context of I5.0 in Sect. 2.2, and presenting research gaps and questions in Sect. 2.3.

2.1 Labor flexibility

LF refers to organizations' capacity to adjust labor capacity, roles, and scheduling practices in response to changing operational demands. LF includes numerical flexibility (adjusting workforce size), functional flexibility (reallocating skills), and temporal flexibility (modifying work time) (Cirillo et al. 2023; Costa et al. 2023a). Within the I5.0 framework, LF is strategic in facilitating human–machine collaboration, which enhances resilience, adaptability, and sustainability (Ivanov 2023; Grosse et al. 2023).

LF's integration with workload control (WLC) is now a central mechanism for reducing inefficiencies while balancing responsiveness and human-centric values (Costa et al. 2023b; Thürer et al. 2024). Adaptive scheduling and multi-skilling help decrease early completions and tardiness, while also enhancing labor engagement and well-being (Henao et al. 2023). Recent simulation studies demonstrate that strategically implemented LF improves system throughput and labor utilization in dual-resource constrained environments (Costa and Portioli-Staudacher 2021; Barkokebas et al. 2023).

While manufacturing continues to dominate in LF applications due to its structured nature, there is a rising trend of cross-sector adoption. For instance, LF facilitates flexible staffing and job rotation in healthcare and hospitality, especially under volatile or crisis conditions (Alemayehu and Tveteraas 2020; Porto et al. 2022). Simulation models indicate that part-time shifts and dynamic task assignment can significantly reduce wait times in emergency departments (Wang et al. 2025c) and improve service quality across labor-intensive sectors. Nevertheless, extending LF beyond manufacturing introduces several complexities, such as skill mismatches, regulatory constraints, and cost–benefit uncertainties (Li et al. 2017; Fang et al. 2025). These challenges emphasize the need for contextualized and operational analyses, which is a primary motivation for focusing on manufacturing in this study.

Research on LF has demonstrated that limited or "moderate" flexibility often provides the greatest operational benefits without overwhelming systems with complexity (Thürer et al. 2020). In constrained settings, optimal labor allocation relies on dynamic decision rules that respond effectively to variability (Wu et al. 2022; Zhang et al. 2022). Strategically implementing LF involves addressing three key questions: When should labor be reallocated? Where should labor be moved? Which labor should be reassigned? These questions underpin the development of tactical labor control policies, cross-training matrices, and simulation-based assessments (Brusco and Johns 1998; Costa et al. 2023a).

2.2 Applicability of LF in practice in the context of I5.0

While the theoretical benefits of LF are well established, its practical implementation remains constrained by organizational, technological, and data-related limitations, particularly in small enterprises (Costa et al. 2023a; Usman and Lu 2024). Effective deployment of LF in I5.0 environments requires the ability to dynamically allocate labor across tasks in response to real-time operational variability. Realizing such responsiveness, however, depends on the availability and integration of reliable operational data, including shop-floor status, task durations, skill assignments, and workforce availability (Razmjoei et al. 2022; Barkokebas et al. 2023).

Recent empirical studies emphasize that the digital maturity of manufacturing systems significantly influences the effectiveness of LF initiatives (Henao et al. 2023;

Rožanec et al. 2023). Small enterprises often face challenges in synchronizing data across systems such as MES, ERP, and workforce management platforms (Tliba et al. 2023). This fragmented integration hinders real-time decision-making essential for supporting the reallocation of a multi-skilled workforce, resulting in suboptimal labor scheduling (Mejía-Moncayo et al. 2024; Wang et al. 2025a).

While simulation models and AI-driven scheduling algorithms have been suggested for exploring the impacts of LF, they frequently depend on idealized data environments. These environments fail to capture the complexities of actual production systems (Gong et al. 2021; Cimino et al. 2025). Consequently, there is insufficient guidance on collecting, validating, and utilizing operational data to support LF strategies in make-to-order (MTO) settings (Ahmadi et al. 2025). This gap is particularly pressing for small enterprises, which encounter resource constraints in both technology adoption and workforce training (Cirillo et al. 2023; Costa et al. 2023b).

While some prior studies have proposed data-related frameworks for WLC or labor allocation (Costa et al. 2023a; Ahmadi et al. 2024), they fall short in providing comprehensive guidance on implementing LF as a complex form of capacity adjustment. For example, previous work presents an information architecture framework for WLC but does not address the operational demands of labor reallocation or the identification of data sources, whether manual, software-based, or hardware-based and lacks a definition of units of measure for workforce-related data (Huang 2017). To bridge this gap, our study introduces FlexiFlow, a structured framework designed to assist small enterprises in mapping, collecting, and integrating the data necessary for LF practices. FlexiFlow guides managers in pinpointing where critical labor-related data resides, measuring it, and integrating it with existing enterprise systems, all while accounting for the resource constraints typically encountered in I5.0 implementations in real-world settings.

2.3 Research gaps and questions

The literature review identifies two primary gaps: first, the need for studies investigating how varying degrees of LF affect idle times, especially in flow shops; and second, the lack of a framework offering practical guidance on acquiring and measuring the data necessary for LF implementation in MTOs. To address these gaps, this study proposes the following research questions (RQs):

> RQ1: How can variable degrees of LF affect idle times in a pure flow shop? Understanding the optimal level of LF helps managers reduce idle time and enhance overall productivity. By determining the necessary amount of flexibility, managers can make informed decisions regarding cross-training and reallocating labor, thereby balancing efficiency with operational costs.
> RQ2: What is the significance of obtaining the necessary input data for the effective implementation of LF in real-world MTO environments, and how can a practical framework be developed to support this process?

The impact of this research lies in its capacity to effectively optimize production processes. A practical framework is proposed to facilitate this optimization through a step-by-step guide on data collection and measurement. This ensures managers have the necessary information for successful LF implementation. In I5.0 environments, integrating advanced technologies within LF frameworks allows real-time data to enhance decision-making for labor allocation, thereby improving accuracy and responsiveness. The RQs aim to address significant gaps in the current literature and offer actionable insights for managers in the manufacturing sector.

The novelty of RQ1 is its focus on quantifying the effects of the LF on idle times, a relatively unexplored area. Understanding these effects is crucial for managers seeking to optimize labor utilization and reduce downtime. RQ2 addresses the practical challenges associated with data acquisition for LF implementation and proposes a comprehensive framework to overcome these hurdles. This research ensures that LF can be effectively applied in actual companies by proposing a structured approach to data collection and its integration with existing systems, particularly those enabled by I5.0 technologies. These contributions are vital for bridging the gap between theory and practice, ultimately enhancing operational efficiency and productivity.

3 Methodology

This section describes the methodology used in this study. Section 3.1 presents the DES model employed to address RQ1, which examines how varying degrees of LF impact idle times and system performance in a stylized flow shop. Section 3.2 outlines the structured process used to develop the FlexiFlow framework, which facilitates the practical implementation of LF and addresses RQ2. For clarity, all notation used in the methodology is compiled in Table 2 of Appendix A.

3.1 Simulation model

The authors employed a DES approach (Banks 2010) using Python and SimPy to investigate the operational dynamics of LF under controlled conditions. Simulation is particularly suitable for this research as it allows for the exploration of dynamic interactions, stochastic behaviors (such as job arrivals and task times), and reallocation strategies that are challenging to capture through analytical or optimization models (Gong et al. 2021; Alam et al. 2023; Cimino et al. 2025). The simulated environment represents a stylized MTO flow shop. Although ‘flow shop’ typically refers to a high-volume, low-variety, automated production system often associated with make-to-stock (MTS) settings, in this study, the authors model an environment more akin to a job shop. It features a dominant sequential flow similar to one-piece-flow production cells commonly seen in low-automation MTO systems. Such environments exhibit high processing time variability and frequent disruptions, making LF particularly applicable. To ensure experimental clarity and isolate the effects of LF, the shop layout is intentionally simplified (Fig. 1). The authors model a U-shaped line consisting of five sequential stations. Each station is operated by a single laborer, with the capacity to accommodate two laborers when flexibility policies are implemented. No

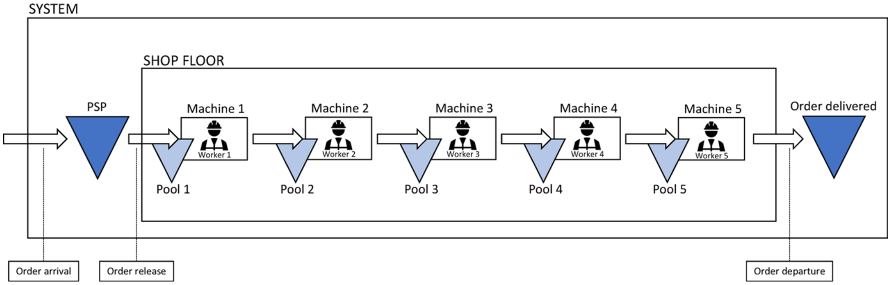

Figure 1 Shop configuration

dual-resource constraints are introduced, allowing for a focused assessment of labor allocation dynamics without the complexity of machine scheduling.

3.1.1 Overview of modelled shop and job characteristics

Each station is modeled as a single resource with the capacity to accommodate two laborers. Consequently, a maximum of two laborers can work at the same station simultaneously. Orders arrive following a Poisson process at a rate of 1.875 orders per time unit. This arrival rate is calibrated to attain a target shop utilization of approximately 93.75% in a fully staffed, five-station system, where each operation averages 0.5 time units for processing. The average processing time is normalized to 0.5 for easier comparison across simulation studies in the WLC and MTO literature (Kingsman and Hendry 2002; Thürer et al. 2016a). Processing times adhere to a lognormal distribution with a coefficient of variation of 0.8, representing the high variability commonly observed in MTO environments. Setup times are assumed to be sequence-independent and are included within the operation processing times. These modeling choices are calibrated to simulate a high-utilization, high-variability MTO flow line, typical of manual, operator-paced production systems, aligning with conventions in WLC simulation literature. This setup allows for the evaluation of LF while considering the realistic variability of the shop floor, where responsiveness is crucial.

3.1.2 Order review and release

Orders in the flow shop are released in a controlled manner. As with previous simulation studies on WLC by Thürer et al. (2016a), it is assumed that all jobs are accepted, materials are available, and all necessary details, such as shop-floor routings and processing times, are known. When order release is applied, jobs are retained in a pre-shop pool (PSP) and are not immediately released to the shop floor; they are held back until they meet specific performance targets.

Various order release methods are documented in the WLC literature, as highlighted by numerous literature reviews (Thürer and Stevenson 2016; Fernandes et al. 2017, 2022). This paper employs a straightforward method that maintains the workload released, but not yet completed, within limits or norms at each station (Oosterman et al. 2000; Thürer et al. 2011; Yan et al. 2016). Where J is the set of jobs in the PSP, and $j \in J$ denotes a single job. Each job (j) has a sequence of operations indexed by , where p_{ij} denotes the processing time of job j at operation . Let s index the stations on the shop floor. W_s refers to the current released workload at station s, and N_s denotes the workload norm (WLN) applied at that station for release control.

At periodic intervals of every eight time units, the following release procedure is executed:

1. Job Sequencing: All jobs in the set of jobs J in the PSP are sorted according to the pool sequencing rule; in this paper, a First Come, First Served (FCFS) dispatching rule is used. The job j in the set J with the highest priority is considered for release first.
2. Job Selection: If job j's processing time p_{ij} at the -th operation at station s, together with the workload W_s released to station s and yet to be completed, fits within the WLN N_s, for each station, then the job j is selected for release. That means it is removed from J, and its workload contribution is included in the W_s of each station; otherwise, the job remains in the PSP, and its processing time does not contribute to W_s. The next job in the PSP is considered for release in the same way until all jobs in the PSP are evaluated for release. Five different WLNs N_s have been used with the highest one, which corresponds to infinite release. The norm is multiplied by the station number to account for the direct and indirect load (Oosterman et al. 2000). Once released to the shop floor, shop progress is controlled by the FCFS dispatching rule.

3.1.3 Levels of labor flexibility and allocation models

The four levels of LF discussed represent a progression from no cross-training to full functionality, aligning with prior simulation studies (Portioli-Staudacher et al. 2020). These levels delineate a range from no flexibility to complete cross-functionality, reflecting common labor deployment strategies in small and medium-sized manufacturing enterprises. Flex1 is characterized by static labor, where laborers remain at their default station. Flex2 introduces moderate flexibility, allowing laborers to operate at their own station and the next downstream station. Flex3 extends this model to include both upstream and downstream stations, whereas Flex5 embodies full flexibility, with laborers cross-trained to perform at any station within the flow shop. Each flexibility level assumes laborers operate at 100% efficiency at every station. Under Flex2, Flex3, and Flex5, labor reassignment occurs if three conditions are fulfilled: the laborer must be capable of operating at the station per the flexibility level, pending workload must exist at the target station, and the station must not already have two laborers assigned (the model permits a maximum of two per station). These reallocation rules simulate reactive assignment practices typically found in low-automation settings, where idle laborers are dynamically redistributed based on visible work-in-process and capacity constraints (Thürer and Stevenson 2016).

Three laborers' assignment models were tested. Model 1 assigns laborers to a default station but allows them to switch when idle, provided the target station has work and fewer than two laborers. Model 2 restricts reassignment to stations exceeding a predefined queue threshold, with various queue lengths tested. Model 3 builds on Model 2 by giving priority to labor already relocated from their default station, ensuring tasks are assigned at the new station unless work becomes available at their original one.

3.1.4 Experimental design and performance measures

The experimental factors comprise: (i) five different WLNs; (ii) four levels of LF (i.e., Flex1, Flex2, Flex3, and Flex5); (iii) 13 levels of queue length; and (iv) three models (i.e., Model 1, Model 2, and Model 3) (Table 1). The selected WLNs (2400, 3000, 3600, 4800, 5400) are based on output control logic, as outlined in prior studies, particularly Oosterman et al. (2000). This work recommends using workload thresholds to control shop-floor saturation. The norms are scaled proportionally, reflecting a range from conservative to liberal release strategies, enabling controlled variation in system load. This approach aligns with other WLC literature (Hendry et al. 1998; Kingsman and Hendry 2002; Costa et al. 2019), where capacity regulation is employed to balance throughput and resource constraints. Queue length values (0 to 100 units) are sampled at 13 levels to systematically represent the full spectrum of shop-floor congestion, from idle to overloaded conditions. This method is consistent with findings from Onay et al. (2023), who emphasize the behavioral impact of perceived queue lengths on operator decisions. Moreover, they underscore that the visibility of work-in-process influences real-time reactions and social norms on the shop floor.

A full factorial design was employed in this study. Data were collected over 500,000 time units, following a warm-up period of 200,000 time units, with 150 runs conducted for each scenario. The system performance measures considered are gross throughput time (GTT), the time between order entry and completion, and shop-floor throughput time (SFTT), the time between order release from the pool and completion. Additionally, the number of labor relocations was assessed. These metrics are commonly used in WLC and MTO simulation literature. GTT and SFTT evaluate overall and internal flow efficiency (Oosterman et al. 2000; Thürer et al. 2016b), whereas labor relocations measure the operational costs of activating flexibility, offering insight into the practical trade-offs of LF implementation (Fernandes et al. 2022).

This study intentionally excludes learning effects and direct cost modeling of LF to isolate the performance implications of task reassignment policies across varying levels of flexibility. Although these aspects are crucial for operational realism, their integration necessitates context-specific data and calibration, which fall outside the scope of this simulation-based design experiment.

Table 1 Design of experiments

Models	1	2	3									
LF	Flex1	Flex2	Flex3	Flex5								
WLN	2400	3000	3600	4800	5400							
Queue length	0	3	5	7	10	15	20	25	30	40	50	70	100

3.1.5 Model validation and verification

The authors undertook standard verification and validation procedures to ensure the simulation results were both reliable and robust. Verification employed common random numbers, ensuring each experimental setup drew from the same stream of customer orders. This method reduced variance caused by random inputs and helped isolate the effects of the experimental parameters. Validation utilized statistical convergence analysis to determine the warm-up period, total run length, and number of replications. Applying the Welch method (Law and Kelton 1991) to GTT indicated that system stabilization occurred after approximately 100,000 min. To ensure accuracy, the authors set the warm-up period to 200,000 min. Each simulation run extended to 500,000 min, leaving 300,000 min, equivalent to about 625 shifts of 8-h each of steady-state data for analysis. To determine the replication count, the authors used the Mean Square Pure Error (MSPE) metric. Figures 4, 5 and 6 in Appendix B demonstrate convergence at approximately 100 runs, which the authors adopted for every configuration. These measures guarded against bias from transient behavior or under-sampling, thus underpinning the credibility of the performance results.

3.2 Framework for LF implementation

To support the practical implementation of LF, we developed FlexiFlow, a structured framework consisting of four data-oriented tables. FlexiFlow is not a software tool, optimization model, or algorithm. Instead, it provides companies with an actionable data architecture framework to identify, source, and measure the input information necessary for LF deployment in both manual and digital shop-floor contexts. The framework was derived from a structured literature-based methodology and contributes to answering RQ2 by offering a scalable tool applicable to various levels of digital maturity. In Sect. 4.2 (Results), the FlexiFlow framework is presented, with a detailed description of its components and implementation rationale.

After assessing the impact of LF on system performance, we developed FlexiFlow to aid companies, particularly those operating under MTO, in gathering the necessary input data for LF implementation. As noted in Sect. 2.2, the foundational research (Huang 2017; Sagawa et al. 2023) initially emphasized the need for structured and comprehensive data for successful LF deployment. This research provided a preliminary list of input data, organized into four tables (Tables 4, 5, 6 and 7), necessary for implementing WLC. Our framework expands and adapts these tables specifically for LF, rather than for WLC in general.

The FlexiFlow tables now consist of four key components: (i) informational entities for LF input control, which detail the essential manufacturing data required to regulate order release; (ii) practical perspectives on LF input control, highlighting implementation challenges and potential solutions; (iii) capacity-related informational entities, which cover data on station and labor availability; and (iv) LF performance measurement entities, which focus on metrics such as tardiness and production yield. While Huang's classification provided a useful baseline, it lacked crucial specifications regarding data sources and units of measurement, which are essential for implementation in both digital and manual contexts.

To address this gap, we enhanced the original tables through a structured literature review, integrating source types and measurement units relevant to companies at various levels of digital maturity (Mušič and Sagawa 2024; Bueno et al. 2025). This updated framework supports both automated data environments and manual data collection practices, facilitating more effective LF implementation across different operational settings.

To determine how companies, particularly digitalized MTO firms, can gather the necessary input data for LF implementation, we performed a two-stage literature analysis that combines narrative and systematic reviews. The initial narrative review, focusing on Scopus-indexed and grey literature, concentrated on digitalized companies and underscored the pivotal role of MESs in supporting LF (Tabim et al. 2024). In digitalized MTO environments, MES facilitates automated real-time input data collection by continuously monitoring shop-floor activities, station performance, and production statuses, typically through sensors and industrial IoT devices (Tariq et al. 2024). These systems improve operational efficiency and provide a data backbone for managing flexible schedules and dynamic labor deployment (Guo et al. 2024).

Building on these insights, we conducted a systematic literature review to examine how MESs and related technologies aid in collecting and managing data necessary for LF implementation. The literature search, as detailed in Fig. 2, was conducted in Scopus and completed on February 29, 2025. We imposed no publication date restrictions during the search phase; thus, the review encompasses relevant publications from any year, provided they met our defined inclusion criteria. Initially, we retrieved 20,811 records using the term “Manufacturing Execution Systems”. We then refined the results by incorporating additional keywords related to MES applications and process adaptation, in line with our focus on data infrastructures essential for LF deployment. Although the search did not directly reference LF, MES applications in adaptive manufacturing processes are highly pertinent due to their integral roles in production monitoring, skill-based scheduling, and resource management.

The search concentrated on the “Engineering” subject area, including only peer-reviewed journal articles and conference proceedings published in English and des-

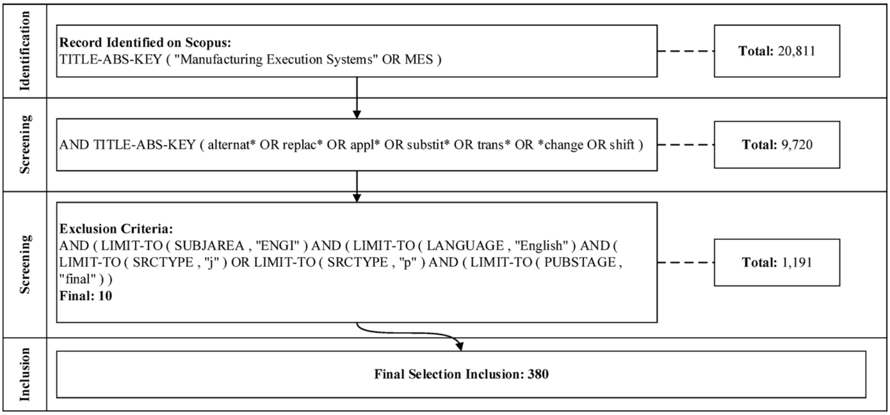

Figure 2 Paper screening process

ignated as “final publications”. Titles and abstracts were screened to exclude studies not directly addressing the digitalization of labor or production processes. The final sample comprised 380 relevant publications, providing a comprehensive and current understanding of how MES technologies support LF practices through real-time data collection, task tracking, and adaptive scheduling. These findings were used to populate and validate the digital data sources integrated into the FlexiFlow framework.

The literature review played a crucial role in identifying existing MES modules and comprehending their roles in data collection, storage, and management, crucial for LF implementation. From the review, several key MES modules emerged. For instance, detailed production scheduling modules facilitate inventory planning, employee assignments based on skill requirements, and capacity scheduling to optimize job sequencing (Tariq et al. 2024; Nejati et al. 2024). Product definition and execution management modules oversee recipe formulation, assembly procedures, flow diagrams, and standard operating instructions, forming the digital backbone of process control (Huang 2017; Sagawa et al. 2023). Reporting modules provide customizable outputs on overall equipment effectiveness, quality metrics, shift activities, and batch records, supporting performance visibility and tracking improvements (Guo et al. 2024).

The review also emphasized the role of data historians, which serve as specialized software components for real-time data logging and long-term storage. These components facilitate the traceability and accessibility of operational data on a large scale (Tabim et al. 2024). After mapping these modules, we connected them to specific data requirements within LF. For example, tracking and data collection modules are crucial in LF, as they provide real-time insights into labor performance, skill deployment, and task completion. These insights are vital for adaptive labor assignment. Through traceability and genealogy functions, these modules convert raw data into actionable inputs, allowing dynamic reallocation (Guo et al. 2024). Furthermore, quality and process monitoring modules identify skill gaps and training needs by capturing detailed performance and conformance data. This allows for targeted and responsive LF strategies. Collectively, these MES modules create a robust data infrastructure that supports flexible workforce deployment and informed labor allocation decisions in real-time production environments (Bianchini et al. 2024; Ahmadi et al. 2025).

In addition to mapping MES modules and their data collection roles, the systematic literature review identified the key infrastructure components, including both hardware and software, that support MES functionality and enable LF implementation. Key infrastructure elements include interface adapters and application servers, which facilitate communication between MES and other enterprise systems (Wang et al. 2023). A core software component, the database, often based on a relational model is responsible for storing and managing complex manufacturing data streams (Bianchini et al. 2024). The literature also emphasizes essential software elements such as database management systems, stored procedures for real-time data processing, and web services that support modular and service-oriented architectures (Tariq et al. 2024). These software components’ modularity and scalability enable MES systems to evolve alongside organizational needs and digital maturity (Ahmadi et al. 2025).

Industry-specific use cases of MESs further illustrate the system's adaptability. Recent applications include dynamic production scheduling and traceability in textile workshops, as well as digital control of inventory and resource planning in discrete manufacturing sectors, such as bicycle assembly (Tariq et al. 2024; Tabim et al. 2024). These findings have been systematically integrated into the FlexiFlow framework. This integration provides companies with a comprehensive summary of input data requirements, source systems (both hardware and software), and units of measurement, tailored specifically to digitalized firms implementing LF through MES infrastructures (Wang et al. 2023).

Since not all companies possess an MES, the literature review explored alternative, manual methods for collecting the input data necessary to implement LF. In addition to the MES-focused systematic review, a narrative review was conducted using grey literature sources. This method broadened the analysis by incorporating diverse perspectives, particularly on manual data collection practices, which are often underrepresented in indexed academic databases. The review included industry reports, documentation from solution providers, and insights from specialized practitioner forums. These sources were consulted to understand the range and application of manual measurement systems in real-world settings (Peinl et al. 2023; Tabim et al. 2024).

By integrating these sources, a more balanced view of both high-tech and low-tech data collection methods was achieved, thus helping to reduce potential publication bias. The narrative review followed explicit selection criteria, incorporating only sources directly relevant to LF implementation in MTO contexts. Attention was particularly focused on capturing various viewpoints regarding workload measurement, operational visibility, and workforce tracking across different levels of digital maturity. This approach revealed practical examples of LF implementation in diverse manufacturing environments, supported by case evidence and deployment strategies from real-world applications (Bianchini et al. 2024). The final FlexiFlow framework integrates the outcomes of both the systematic and narrative literature reviews, providing a comprehensive and context-sensitive reference for companies aiming to implement LF across various digitalization levels.

4 Results and framework development

This section presents the two main outcomes of the study, each aligned with the RQs defined in the introduction. Section 4.1 addresses RQ1 by reporting the results of the DES, which explores the impact of various LF models, queue length limits, and WLNs on GTT, labor relocations, and overall system performance. Section 4.2 responds to RQ2 by introducing FlexiFlow, a practical, data-oriented framework designed to support the implementation of LF strategies in manufacturing environments. Building on the simulation findings, FlexiFlow provides structured guidance for companies to collect, prioritize, and utilize necessary operational and performance data, aiming to enable human-centric labor adaptability in alignment with I5.0 principles.

4.1 Impact of LF on shop-floor performances

Figure 7 illustrates the increase in GTT as the queue length expands from zero to 100, based on Model 2. When the queue length is zero, no constraints are applied to labor relocation (Model 1). Figure 8 demonstrates that when the queue limit is set to zero, the GTT reaches its minimum level, coinciding with the peak in relocations. As the queue length increases, the likelihood of laborers being relocated diminishes, leading, as anticipated, to a deterioration in the GTT. The findings indicate that for all the WLNs tested, the GTT deteriorates as the queue lengthens. Higher WLNs result in a greater GTT because more workload is released onto the shop floor. This pattern is similarly observed across other levels of LF tested (Flex2 and Flex5).

The deterioration of the GTT is not linear; instead, the GTT increases with a negative slope. Laborers are relocated only when another station's workload surpasses a predefined threshold (queue limit on the x-axis). This implies that relocations do not occur as soon as laborers become idle, as illustrated by Model 1, which features a queue level of zero. Figure 9 provides additional information on the number of relocations over the simulation period (300,000 time units). The authors report the highest number of relocations when using Model 1, indicated in the graph at the point where the queue length is zero. As Fig. 9 demonstrates, implementing Model 1 on shop floors would be challenging due to the high frequency of labor relocations, exceeding 35,000 relocations within 300,000 time units, despite its optimal lead time performance.

Figure 10 illustrates the significant reduction in relocations when applying Model 2, which involves transferring laborers only when the workload at other stations exceeds the queue limit (x-axis). With a minimum queue level of 20 time units, corresponding to a small increase in the GTT, relocations are reduced by more than 7 times, falling below 5000. This scenario is replicable in real-world companies. The Flex3 strategy increases GTT by 14% while reducing labor relocations by 43%. Implementing smaller queue length limits further decreases relocations with only a slight increase in GTT.

Figure 11 illustrates the percentage reduction in GTT achieved under various levels of flexibility. In Model 1, where the queue length is zero, significant improvements in GTT occur primarily when transitioning from Flex2 to Flex3. Model 2 exhibits similar trends; however, as the queue length increases, the benefits of transitioning from Flex2 to Flex3 become comparable to those from Flex1 to Flex2. With Model 2, a low queue length results in substantial reductions in relocations, while maintaining most of the GTT benefits. Even minimal flexibility effectively reduces GTT. Flex5, offering the highest flexibility, delivers the optimal GTT performance. Notably, there is already a substantial GTT improvement of at least 40% with the transition from Flex1 to Flex2, as depicted in Fig. 11. Advancing to Flex3 enhances GTT further, reaching at least an 80% reduction. The shift to Flex5 offers a slight additional improvement in GTT.

Figure 12 illustrates that Flex5 exhibits the lowest GTT. Nevertheless, it also shows the highest number of relocations, reinforcing the findings in Fig. 11. This indicates that cross-training from Flex3 to Flex5 offers marginal improvements in GTT while significantly increasing labor movements. The curves for Flex3 and Flex5 nearly overlap across most WLN levels, indicating diminishing returns beyond Flex3. Building on Model 2, Model 3 incorporates a rule that prioritizes assigning laborers to their current station if they have already been relocated from their default station and no jobs are available at the original station. As shown in Fig. 12, Model 3's GTT performance is comparable to Model 2. When the queue length is zero, Model 2 slightly outperforms Model 3. However, as queue length increases, Model 3 begins to surpass Model 2 in terms of GTT performance.

Figure 13 demonstrates that Model 3 consistently results in fewer labor relocations than Model 2, particularly at shorter queue lengths. This trend is further supported by Fig. 14, where Model 3 shows a more favorable trade-off between GTT and the number of relocations. As depicted in Fig. 15, Model 3 achieves similar reductions in GTT with fewer relocations compared to Model 2. This improvement is due to Model 3's rule-based reassignment logic, in which laborers are not returned to their original stations unless a job is available there. This strategy minimizes unnecessary movements and enhances relocation efficiency.

As further evidenced in Fig. 16, Model 3 demonstrates superior performance at low queue lengths. It achieves substantial GTT improvements with minimal relocations, making it a realistic and applicable option for real-world shop floors, particularly for reallocating labor for small or short tasks.

4.2 FlexiFlow framework

Complete job data is crucial for improving lead time and includes factors such as job quantity, production stages, setup and processing times, and operators' skills. To assist companies in collecting and managing this data, the FlexiFlow framework has been developed. FlexiFlow aims to guide companies in implementing LF practices

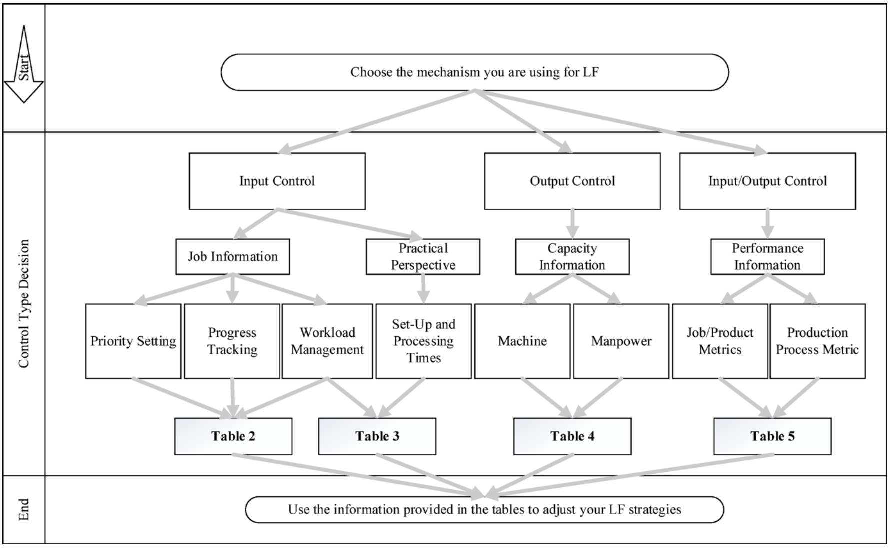

Figure 3 The FlexiFlow framework is used to support companies in implementing LF

to optimize lead time, as discussed in the previous section. The framework integrates information from four interconnected data tables located in Appendix E. These tables cover job-related informational entities, practical perspectives on challenges in collecting job-related data along with proposed alternative solutions, capacity-related informational entities, and performance-related informational entities. They specify not only the data companies should collect but also the sources for obtaining this data and the appropriate measurement units necessary for LF implementation.

Before discussing Tables 4, 5, 6 and 7 in Appendix E, Fig. 3 presents a decision-making framework integrated into FlexiFlow. This framework assists companies in navigating the four tables by helping them identify the pertinent data for LF implementation based on the specific workload mechanism they intend to use.

In more detail, while LF generally involves managing workload by allowing operators to move between stations and thereby temporarily boosting output at a specific station without adding extra capacity to the system, its use depends on the implemented workload mechanism: input control, output control, or both. Input control governs the release of new orders into the manufacturing system, impacting the necessity for labor mobility and serving as a basis for planning LF. Conversely, output control directly adjusts production capacity by reallocating laborers across stations according to predefined rules, forming the core of the LF strategy.

Figure 3 streamlines the LF implementation process, guiding companies through the four data tables based on the chosen workload mechanism. According to Fig. 3, when a company focuses on input control, it should prioritize collecting “job information”, such as priority setting, progress tracking, and workload management. For these tasks, FlexiFlow recommends consulting Table 4. If challenges arise in acquiring certain job-related data (indicated with an asterisk in Table 4 based on earlier work), companies can utilize “practical perspectives” that offer alternative solutions, such as information on setup and processing times, with FlexiFlow guiding them to Table 5 (Huang 2017). Conversely, when the focus is on output control, companies should emphasize gathering “capacity information” to optimize machine and labor utilization, with FlexiFlow directing them to Table 6.

Finally, whether companies implement input control, output control, or both mechanisms, LF “performance information” should be collected to evaluate metrics like tardiness, throughput, and efficiency. For this purpose, FlexiFlow advises consulting Table 7.

Tables 4, 5, 6 and 7 provide a detailed summary of the data necessary for implementing LF. Each table is structured into five columns to offer comprehensive guidance. The first column enumerates the informational entities essential for planning LF strategies. The second column describes the relationship between each informational entity and LF, justifying the necessity of the data. The third column specifies the recommended units of measurement, including alternative options when applicable. The fourth column details data sources, which can be manual or automated. This versatility allows companies to gather actionable information according to their technological readiness. FlexiFlow caters to firms across the digitalization spectrum, from those with advanced MES systems to those using manual data collection methods. For companies without MES, FlexiFlow recommends manual processes like scheduling boards, operation time logs, and labor skill assessment forms. Conversely, for digitalized companies, it suggests both hardware and software solutions for data acquisition. On the hardware side, FlexiFlow advises on technologies and equipment necessary for automated data collection and effective MES utilization. For software, it identifies MES modules such as job order tracking, labor management, and real-time performance analytics to streamline LF implementation. The fifth column of Tables 4, 5, 6 and 7cites scientific literature to validate the preceding content.

Each table in the study serves a unique purpose. Table 4 focuses on the informational aspects of manufacturing jobs, including routing and operational workload data. This data is crucial for optimizing LF strategies. According to Table 4, understanding job routing specifically the capacity resources needed for manufacturing tasks in sequential order enables the efficient allocation of skilled labor to meet job requirements. Routing is typically measured in units produced or capacity and can be sourced from manual systems such as routing sheets or automated tools like scheduling software used for planning and tracking.

In another instance, knowing a job's priority, defined by factors such as urgency, complexity, and profitability, allows for the proper allocation of labor in terms of quantity and skill set to maintain customer service levels and meet deadlines. Job priority is usually non-dimensional, with qualitative levels like “normal” or “high”, and can be determined manually by consulting documents such as priority-setting protocols or automatically via MES modules like the Order Management Module.

Table 5 provides practical strategies and alternative informational solutions to help companies access job-related information when facing challenges with the data presented in Table 4. Specifically, for informational entities affected by unexpected shifts in demand or production uncertainties, Table 5 explores how companies manage job quantities and production times. This management facilitates the reallocation of labor to address unforeseen increases in production demand, thereby ensuring operational flexibility. Such adjustments are monitored using either manual or automated tools that offer real-time updates to production logs. In terms of automated tools, pertinent MES modules may include job order tracking and labor-management systems.

Table 6 focuses on capacity-related informational entities, specifically examining machine capacity and labor. It highlights the importance of laborers' abilities to operate diverse machines and adapt to various functions. This adaptability ensures effective labor usage across different shifts and tasks. By integrating human flexibility with autonomous technologies as demonstrated in human–robot collaborative workflows propelled by digital twins (DTs) the potential to enhance system robustness while addressing operational uncertainties is underscored (Wang et al. 2024). The table merges manual methods and hardware systems to monitor and optimize machine and labor usage, supplemented by software for resource allocation and status updates.

For instance, Table 6 suggests collecting data on the machine-man-hour ratio, measuring the number of man-hours performed per machine hour. This data aids in planning LF strategies that optimize machine usage while minimizing labor requirements. Typically expressed in man-hours per machine hour, this information can be collected manually through man-hour logs and operation time sheets or automatically using a combination of hardware (e.g., workstation computers and time-tracking devices) and software (e.g., MES resource allocation and status module, database systems, and data analytics tools).

Table 7 lists performance-related informational entities that companies can monitor to assess the effectiveness of LF strategies. These entities include job- and product-related metrics, such as tardiness, and process-related metrics, such as SFTT. For instance, Table 7 suggests monitoring tardiness as a job- and product-related metric. Tardiness highlights jobs where actual deliveries occur later than promised due dates, measured either as a percentage of total deliveries or as the average duration of delays. Thus, tardiness offers insights into the effectiveness of LF in reducing production delays and meeting deadlines. Data for measuring tardiness can be collected manually, using logs and problem resolution records, or automatically, employing software solutions like real-time analytics software, database systems, and data analytics tools, supported by hardware such as workstation computers and mobile devices.

To better assist readers in utilizing FlexiFlow, we present a case study application as an example below.

4.2.1 Case study application of flexiflow

This case study illustrates the practical application of the FlexiFlow framework, showing how readers can utilize Fig. 3 as a decision guide and navigate Tables 4, 5, 6 and 7 based on control strategies, input, output, or both. Company A provides an example of how to determine necessary data, consult the relevant table, and apply either manual or automated tools according to the company's level of digital readiness. This example offers a tangible roadmap for practitioners and researchers who aim to implement LF with FlexiFlow in their own settings.

Consider Company A, a small Dutch company as described by De Leede et al. (2020). This company employs 65 mechanics who specialize in installing preventive maintenance equipment and in MTO production for German firms. Although Company A faces fairly predictable national demand, it encounters significant demand peaks in various Dutch regions (De Leede et al. 2020). To manage these demand fluctuations, Company A employs two strategies: (i) allowing mechanics to schedule their own jobs to control the release of new orders (input control in Fig. 3); and (ii) reallocating mechanics across Dutch regions to address local demand peaks without increasing total working capacity (output control in Fig. 3). As noted by De Leede et al. (2020), the company trains all mechanics to handle any task but aims to reduce labor stress and maintain service quality by minimizing regional relocations.

Company A has not yet adopted LF strategies and remains unaware of the corresponding data requirements. Although considering an MES, it currently lacks advanced technology. FlexiFlow offers a solution by providing the necessary data for implementing LF and facilitating an understanding of how MES can automate data collection and identify the required MES modules for each data type. As Fig. 3 indicates, Company A should consult Tables 4, 5, 6 and 7 while using FlexiFlow. To determine the data needed for input control, such as job quantity, delivery date, and job priority, it is recommended to first review Table 4. This information aids mechanics in preparing job scheduling (or routing).

In an MTO environment, where each product features unique setup and production times, accurately recording and analyzing these times is crucial for reducing idleness and optimizing workload, including the allocation of laborers to stations. To correctly gather data listed in Table 4, FlexiFlow suggests that if Company A invests in an MES, digital modules such as a maintenance management system can be used for real-time tracking, with manual logs supplementing information not captured by software. This ensures comprehensive data access, even in less digitalized environments.

Additionally, Fig. 3 advises consulting Table 5 for practical solutions to address job data variability. For example, because Company A's setup times may fluctuate owing to unexpected events, tracking the average setup time is essential for optimizing workload and LF processes. A maintenance management module can calculate average times, while manual logs can provide backup in non-digitized instances. Subsequently, Fig. 3 recommends utilizing Table 6 to obtain capacity data, which should be combined with Tables 5 and 6 to formulate LF strategies. Company A can strategically plan operator relocations to align with regional capacity needs and minimize movements based on job schedules and labor efficiency, recognizing that each laborer is skilled in performing each task.

Furthermore, Company A can leverage MES labor-management modules to monitor labors' primary and secondary skills, which are numerically rated, aiding in job assignments that match these skills. By efficiently aligning priority jobs (as outlined in Table 4) with appropriately skilled labor, Company A can enhance its performance.

FlexiFlow utilizes Table 7 to track key performance indicators (KPIs), enabling Company A to evaluate LF efficiency and take action when standards are not met. For instance, Company A prioritizes maintenance, making job tardiness and lateness critical for maintaining customer satisfaction and preventing failures. By connecting real-time analytics software to station computers, managers can monitor delivery performance, identify delays, and enact corrective measures.

Data on performance, whether collected digitally or through manual logs, provides insights into production bottlenecks. This information helps optimize operations and ensure tasks are completed on schedule. The FlexiFlow framework assists Company A in acquiring the necessary data to implement LF strategies. It leverages the mechanics' skills and reduces unnecessary relocation, creating adaptable and resilient production environments. FlexiFlow offers comprehensive data collection guidance, prioritizing data sources based on Company A's existing infrastructure. It identifies necessary data, suggests appropriate units of measurement, and integrates both manual and digital practices for seamless compatibility with MESs. Although FlexiFlow recommends manual data collection due to the absence of an MES at Company A, it also identifies valuable modules should the company decide to install an MES. This guidance aids in the standardization and integration of data from automated sources, supporting Company A's transition towards digitalization.

FlexiFlow's adaptability allows Company A to apply LF across various technological contexts without requiring a complete system overhaul. Its streamlined data requirements are another significant advantage. Tables 4, 5, 6 and 7 comprise the complete and essential dataset for LF implementation. This focus on relevant data collection prevents unnecessary expenditure on redundant MES modules and associated hardware, thereby conserving both time and resources. Additionally, Flexi-

Flow aligns with I5.0's goal of creating human-centered, tech-integrated systems. By reducing errors in data collection and analysis, operations improve, as does labor welfare, for example, minimizing the relocation of mechanics at Company A.

5 Discussion

The results of this research align closely with existing literature, particularly the principles of I5.0. These principles emphasize integrating advanced technologies with human-centric methodologies to create adaptable, resilient, and sustainable production environments. I5.0 represents a shift from the technology-driven framework of Industry 4.0, positioning human laborers as central collaborators with smart systems to optimize performance and flexibility. This study's exploration of LF in an MTO directly supports I5.0's objectives, highlighting the necessity of efficient human–machine collaboration to enhance productivity and reduce inefficiencies in dynamic production settings.

The simulation-based experiments provide quantitative insights into the effects of different levels of LF and relocation rules on lead time and labor utilization. Our findings indicate that moderate cross-training (Flex3), when combined with controlled relocation strategies (Models 2 and 3), achieves significant reductions in GTT (up to 80%). Furthermore, it markedly decreases unnecessary labor movements by over 40% in certain configurations. These results have important implications for balancing productivity with workforce well-being. For instance, Flex5 offers only slight improvements beyond Flex3, while significantly increasing labor relocations and training complexity. This supports the I5.0 principle that maximizing human potential does not necessitate heightened labor mobility but rather smartly constrained flexibility, tailored to the specific context.

From a managerial perspective, this finding presents a practical approach to enhancing workforce adaptability. Instead of implementing full multi-skilling across all stations, which can be expensive, time-consuming, and disruptive, organizations can concentrate on targeted cross-training and queue-based labor mobility to optimize workflow without overwhelming employees. Managers can employ queue thresholds and WLNs as tools to refine reallocation strategies under varying workload conditions. Furthermore, our results indicate that even modest enhancements in digital infrastructure, such as basic IoT-based monitoring, can enable dynamic reallocation rules to work effectively on real-world shop floors.

The FlexiFlow framework, validated through a case study with Company A, addresses the disparity between simulation outcomes and organizational readiness for implementation. Many firms lack the structured data or digital maturity required to effectively employ LF strategies. FlexiFlow bridges this gap by guiding companies in identifying, collecting, and prioritizing data according to their workload mechanism, whether input, output, or both, and connecting this data to either manual or MES-supported systems. It functions as both a decision-support tool and a scalable digital architecture, accommodating firms at various technological readiness levels. For Company A, a small Dutch firm without advanced MES capabilities, FlexiFlow facilitates gradual LF implementation while minimizing disruptions to operations and training.

Our findings confirm key insights from previous LF literature, particularly the productivity benefits of multi-skilled labor and adaptive scheduling (Mantravadi et al. 2023). However, our results challenge the prevailing assumption that increased flexibility always enhances performance. Whereas previous studies have recognized the coordination burden associated with excessive flexibility (Shojaeinasab et al. 2022; Baier et al. 2024), few have quantified its diminishing returns. Through simulations of various flexibility levels, we demonstrate that Flex3 consistently outperforms both lower and higher configurations. This finding reveals a practical threshold where most performance gains are achieved without overburdening employees.

By conducting this study, we extend the literature by offering a simulation-based validation of the LF-efficiency trade-off within dynamic and stochastic shop-floor conditions. This contribution adds empirical depth to the ongoing conceptual debates around 'smart flexibility' in human-centric systems.

Additionally, our approach incorporates human variables, including task fatigue, queue exposure, and relocation frequency, aligning with recent research on sustainable digital transformation (Alam et al. 2023). These elements underscore the importance of designing LF systems that are efficient, resilient, and sustainable in real-world applications.

Our use of predictive and prescriptive analytics within a DES framework aligns with recent proposals advocating for bi-directional synchronization between the physical and digital layers of manufacturing systems (Santos et al. 2020). Through FlexiFlow, we contribute to implementation literature by providing a practical information architecture framework that facilitates LF adoption across companies with varying levels of digital readiness. Unlike previous frameworks, which often assume the presence of MES or DTs, FlexiFlow offers a data-light pathway to implementation. This approach is particularly relevant for small firms transitioning to I5.0. Thus, our study bridges the gap between theoretical models and real-world applicability, addressing recent calls for actionable and inclusive LF strategies.

6 Conclusion

This study presents a structured simulation-based evaluation of LF strategies in MTO environments and introduces the FlexiFlow framework to facilitate their implementation. The simulation results demonstrate that moderate cross-training and queue-based labor reallocation rules (e.g., Flex3 with Model 2) can significantly reduce lead times by up to 80%, while minimizing unnecessary labor relocations. These findings highlight the value of smart, context-sensitive flexibility over a fully generalized approach to labor mobility, aligning with I5.0's human-centric principles.

To support real-world applications, the FlexiFlow framework provides a practical roadmap for companies to identify, collect, and prioritize essential LF-related data. It offers guidance for both manual and digital environments, enabling firms to focus on actionable information for managing input and output workloads. A case study featuring Company A illustrates how FlexiFlow can be utilized by organizations with limited digital maturity. However, the framework has not yet undergone complete pilot in an industrial setting. Its design is informed by empirical patterns and practitioner-oriented logic, but further application and testing across various industries are needed to verify its impact and adaptability.

This study has several limitations. The simulation assumes uniform labor efficiency in its initial configurations and is currently restricted to pure flow shop settings. Future research should expand to include job shops, heterogeneous skill profiles, and dynamic efficiency curves. Additionally, industrial validation of the FlexiFlow framework, including stakeholder feedback and implementation constraints, remains a crucial next step to enhance the practical utility of the proposed approach. By bridging digital technologies with operational decision-making and workforce adaptability, this research contributes both conceptually and practically to the evolving field of I5.0.

The FlexiFlow framework holds potential for enhancement through the integration of DT technologies. Such integration could facilitate real-time synchronization between operational data and labor allocation logic. By incorporating predictive capabilities and models of human–machine collaboration, DTs can improve the responsiveness and adaptability of LF strategies. This approach aligns with recent advances in human-centric DT ecosystems (Minerva et al. 2020) and represents a promising evolution of our framework within high-maturity I5.0 contexts.

Appendices

Appendix A: Notation Table

See Table 2.

Table 2 Table of notations listing all symbols used throughout the methodology

Symbol	Definition
	Set of all jobs in the pre-shop pool (PSP)
$\in J$	Index for a single job
	Index for operations in a job
p_{ij}	Processing time of job j at operation i
s	Index for stations on the shop floor
W_s	Current released workload at station s
N_s	WLN at station s for release control
FCFS	First Come, First served dispatching rule
GTT	Gross throughput time (order entry to completion)
SFTT	Shop floor throughput time (release to completion)
MSPE	Mean square pure error used for determining replications

Appendix B: MSPE Convergence for Performance Metrics

See Fig. 4, 5, 6.

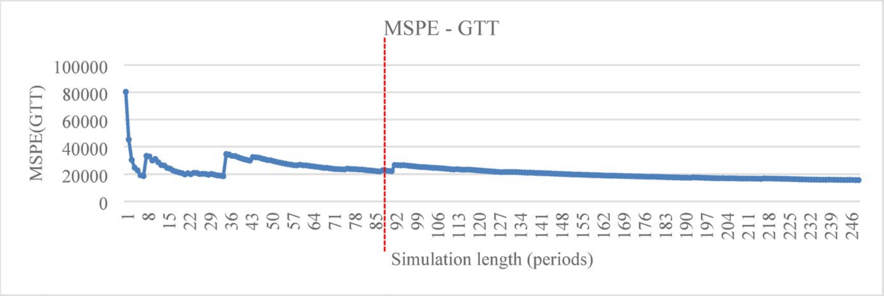

Fig. 4 GTT means square pure error convergence

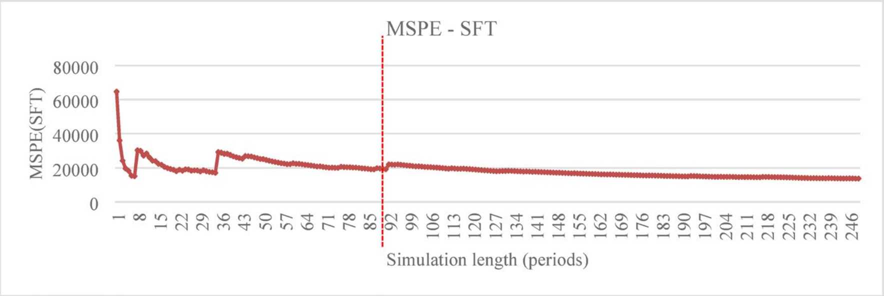

Fig. 5 SFT means square pure error convergence

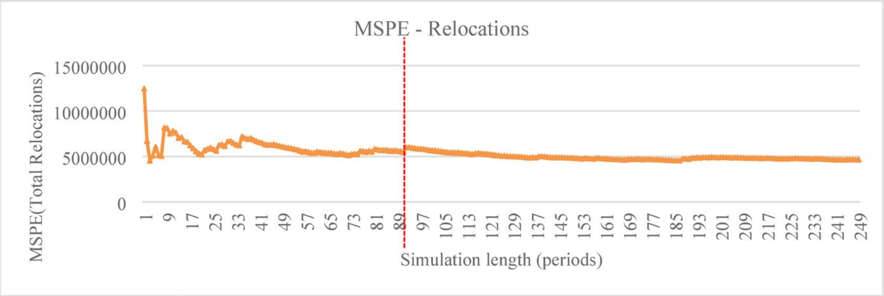

Fig. 6 Relocations means square pure error convergence

Appendix C: Analysis of Variance (ANOVA)

To statistically assess the significance of the simulation results, we conducted an ANOVA on the GTT for Model 3, which represents the most behaviorally nuanced labor reallocation strategy considered in our study. This model includes all major experimental factors: LF level, WLNs, and queue length limits, making it ideal for evaluating interaction effects and main factor significance:

- LF: Flex1, Flex2, Flex3, Flex5
- WLN: 2400, 3000, 3600, 4800, 5400
- Queue Lengths: 0, 3, 5, 7, 10, 15, 20, 25, 30, 40, 50, 70, 100

Simulation outputs from all combinations of these levels (5 WLNs × 4 Flex levels × 13 Queue Lengths) were analyzed using Minitab. The resulting ANOVA Table 3 shows that all main effects and most two-way interactions are statistically significant, as evidenced by *p*-values < 0.05, using a 95% confidence level. These results confirm that each of the three experimental factors exerts a meaningful influence on GTT, and that their combinations can produce non-linear interaction effects, further validating the relevance of the simulation setup and findings.

See Table 3.

Table 3 ANOVA output

Source	DF	Adj SS	Adj MS	F-Value	*P*-Value
LF	2	401,264,147	200,632,073	1068.99	< 0.0001
WLN	4	106,383,801	26,595,950	141.71	< 0.0001
Queue lengths	12	2,094,243,253	174,520,271	929.86	< 0.0001
LF*WLN	8	5,966,774	745,847	3.97	< 0.0001
LF*Queue lengths	24	176,645,693	7,360,237	39.22	< 0.0001
WLN*Queue lengths	48	92,231,860	1,921,497	10.24	< 0.0001
Error	19,400	3,641,065,599	187,684		
Lack-of-Fit	290	6,820,874	23,520	0.12	1000
Pure error	19,110	3,634,244,725	190,175		
Total	19,499	6,520,947,642			

Appendix D: GTT, Queue Limits, and Relocation Trade-offs

See Figs. 7, 8, 9, 10, 11, 12, 13, 14, 15 and 16.

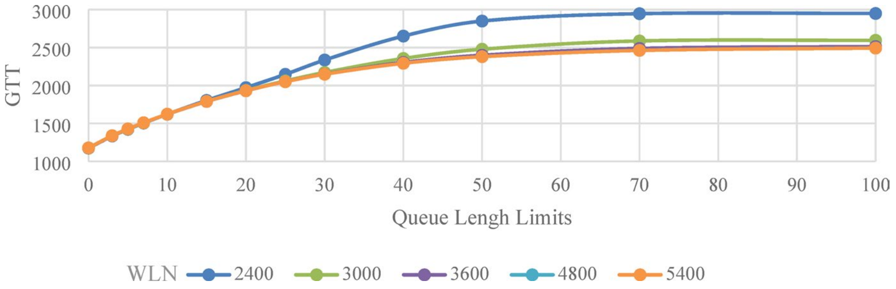

Fig. 7 Queue length limits versus GTT by WLN for Model 2, Flex3

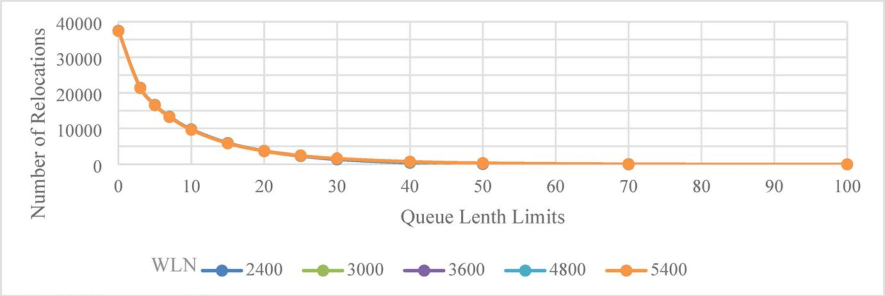

Fig. 8 Queue length limits versus the number of relocations by WLN for Model 2, Flex3

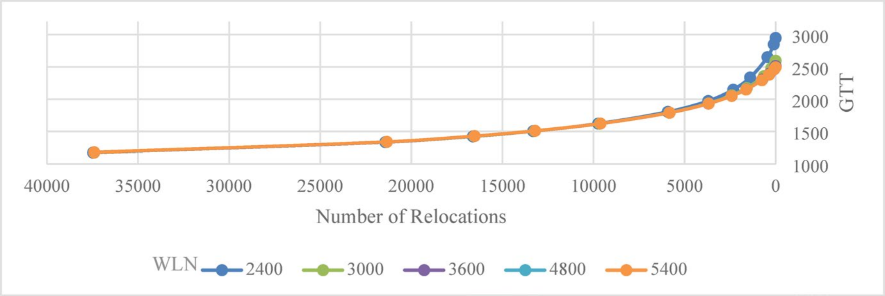

Fig. 9 Number of relocations versus GTT by WLN for model 2, Flex3

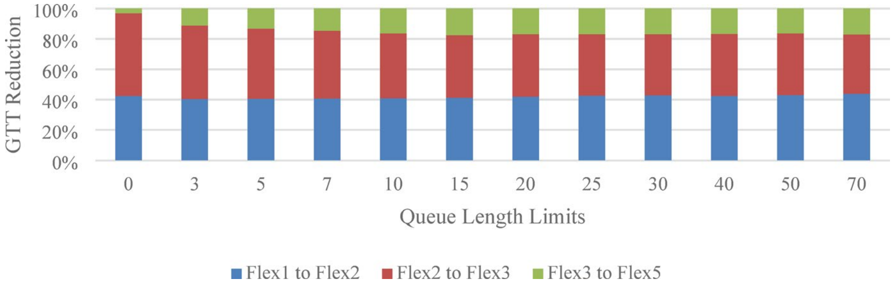

Fig. 10 Composition of GTT reduction for different flexibility levels by queue limit for model 2

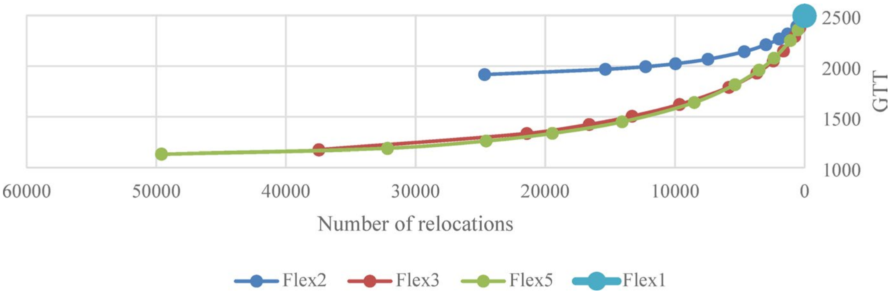

Fig. 11 Number of relocations versus GTT by flexibility level for model 2

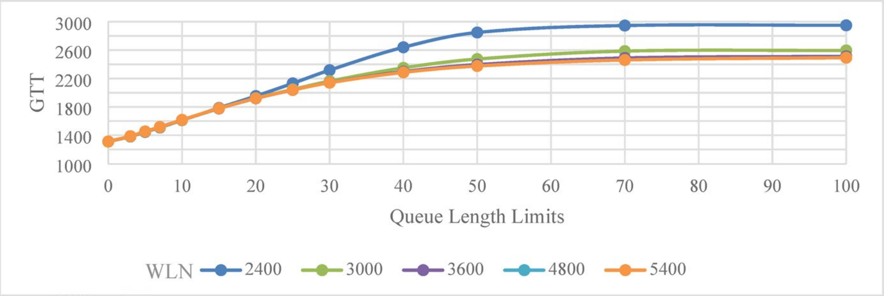

Fig. 12 Queue length limits versus GTT by WLN for Model 3, Flex3

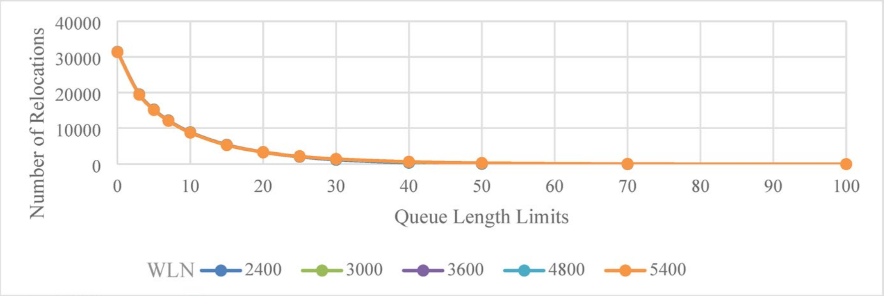

Fig. 13 Queue length limits versus number of relocations by WLN for Model 3, Flex3

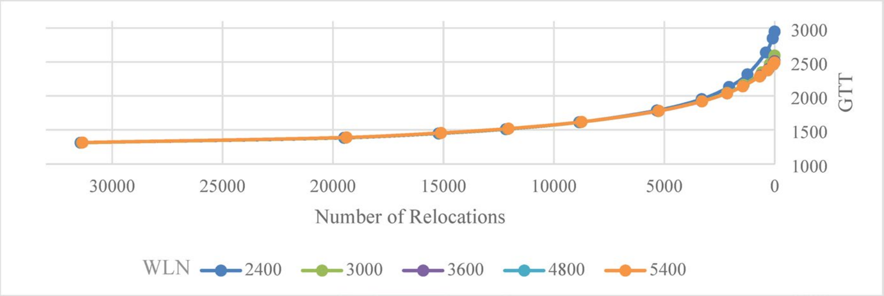

Fig. 14 Number of relocations versus GTT by WLN for model 3, Flex3

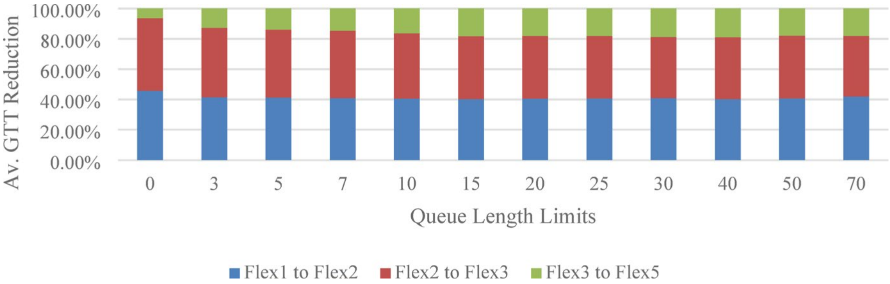

Fig. 15 Composition of GTT reduction for different flexibility levels by queue limit for model 3

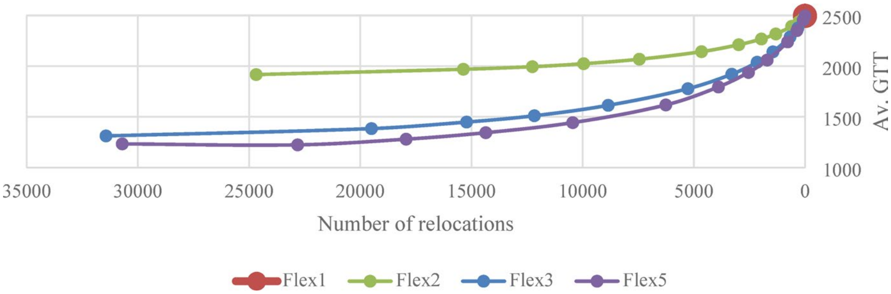

Fig. 16 Number of relocations versus GTT by flexibility level for model 3

Appendix E: Data Requirements and Sources for LF Implementation

See Tables 4, 5, 6 and 7.

Table 4 Job-related informational entities for LF implementation

Informational entity		Relation to LF	Units of measurement	Data sources			References
				Manual system	Hardware	Software	
Routing (Estimated)	Work centres, Operational sequence	Allocating skilled laborers to different work centers as per job requirements enhances resource optimization and ensures that LF reflects operational sequencing and capacity utilization effectively	Units produced / Capacity units	Routing sheets, Workload logs	Workstation computers, Network infrastructure, Database system	Scheduling and planning module, Application programming interface, Data analytics tools	Chen et al. (2021)
Operation workload (Estimated)	Setup time*	Reducing setup time by adapting to different machines/processes quickly minimizes LF variability, ensuring smoother production transitions	Time	Setup time logs, Event-driven checklists	Workstation computers, Timers or stopwatches, Mobile devices	Maintenance management module, Database system, Data analytics tools	Mantravadi et al. (2023)
	Processing time*	Managing varying processing times through LF ensures resources are dynamically allocated to meet demand fluctuations, minimizing idle labor or bottlenecks	Time/Unit	Operation time logs, Batch records	Workstation computers, Sensors and data loggers, Timers or stopwatches	Performance analysis module, Database system, Data analytics tools	Shojaeinasab et al. (2022)
	Job quantity** (Produced items)	Adjusting labor in response to changes in job quantity stabilizes LF and avoids underutilization or overburdening of available resources	Number of units	Job order logs, Production scheduling boards	Workstation computers, Barcode scanners	Order management module, Database system, Data analytics tools	Peinl et al. (2023)
Progress status (Actual)	Enquiry date	Ensuring availability of skilled laborers for new jobs proactively balances LF before job acceptance	Date	Enquiry logs, Customer interaction records,	Workstation computers, Enquiry panel	Order management module, Database system, Data analytics tools	Jaskó et al. (2020)
	Confirmation date	Mobilizing the labor quickly after job confirmation ensures LF reflects real-time production priorities	Date	Confirmation log books, Digital spreadsheets	Workstation computers, Scanners, Data entry devices	Order management module, Database system, Data analytics tools	Chen et al. (2021)
	Material arrival date	Assigning laborers as materials arrive ensures LF dynamically adjusts to inventory inflows, preventing delays	Date	Material arrival logs, Inventory spreadsheets	Workstation computers, Barcode scanners, Mobile devices	Inventory management module, Database system, Data analytics tools	Bianchini et al. (2024)

Table 4 (continued)

Informational entity		Relation to LF	Units of measurement	Data sources			References
				Manual system	Hardware	Software	
	Contractual due date	Meeting due dates through dynamic labor reallocation reflects LF's role in ensuring adherence to contractual obligations	Date	Contract files, Due date calendars, Schedule boards	Workstation computers, Document scanners	Scheduling and planning module, Contract management module, Database system, Data analytics tools	Da Costa Dias et al. (2021)
	Job release date	Starting jobs promptly upon release ensures LF is updated to accommodate new workloads without delays	Date	Job release logs, Production scheduling boards	Workstation computers, Barcode scanners, RFID readers	Inventory management module, Database system, Data analytics tools	Mantravadi et al. (2022)
	Completion time*	Optimizing operation completion times reflects LF's role in ensuring timely production and maintaining workflow continuity	Date	Operation completion log, Time sheets	Workstation computers, Clocks or timers, Sensors and data loggers	Production tracking module, Database system, Data analytics tools	Saenz de Ugarte et al. (2009)
	Delivery date	Meeting delivery dates through efficient production ensures LF captures performance targets and delivery reliability	Date	Delivery logs, Delivery confirmation records	Workstation computers, GPS trackers, Delivery scanners, Mobile devices	Order management module, Database system, Data analytics tools	SAP (2023)
Priority setting	Job priority (Estimated)	Allocating the right amount and skill set of labor based on job priority ensures LF reflects criticality levels, enhancing responsiveness to urgent tasks	Non-dimensional (levels of criticality established like Normal / High)	Priority setting protocols, Job tracking spreadsheets, Visual scheduling boards	Workstation computers, Network infrastructure, Database system	Order management module, Rules-based system, Database system, data analytics tools	Zwolińska et al. (2020)

*Data that are 'nice-to-have' but difficult to obtain in practice; **data that are over-simplified in the design of the LF concept

Table 5 Practical perspectives for job-related data gathering

Informational entity	Relation to LF	Units of measurement	Data source			References
			Manual system	Hardware	Software	
Job quantity	Reallocating labour to handle unexpected increases in job quantity ensures LF dynamically adjusts to fluctuations in demand, preventing overburdening or underutilization of labor resources	Number of units	Production logs, Batch records	Workstation computers, Barcode scanners, Scales or counting devices	Order management module, Database system, Data analytics tools, Quality control software	Mantravadi et al. (2023)
Operation setup times	Adapting quickly to different setup requirements and transitions minimizes setup time, stabilizing LF and maintaining smooth workflow across operations	Time	Setup logs, Time recording sheets	Workstation computers, Timers or stopwatches	Maintenance management module, Database system, data analytics tools	Chen et al. (2021)
Operation processing times	Dynamically allocating labor based on actual processing times ensures LF reflects real-time performance, optimizing resource allocation and avoiding inefficiencies	Days or hours per operation	Operation time logs, Expert estimation records	Workstation computers, Timers or stopwatches, sensors and data loggers	Performance analysis module, Database system, Data analytics tools	Shojaei-nasab et al. (2022)
Operation completion time	Enabling quick responses to changes or delays in operation completion ensures LF tracks delays accurately, allowing timely adjustments to maintain workflow continuity	Time or date	Manual time logs, End-of-operation checklists, Timestamps on operational documents	Workstation computers, Clocks or timers	Production tracking module, Database system, Basic digital tools	Saenz de Ugarte et al. (2009)

Table 6 Capacity-related informational entities

	Informational entity	Relation to LF	Units of measurement	Data source			References
				Manual system	Hardware	Software	
Machine capacity	Work center (Operation function)	Ensuring laborers are skilled in operating different machines or adapting to various operational functions enables LF to reflect operational flexibility and machine utilization efficiency	Units produced/Capacity units	Machine operation logs, Machine efficiency checklists, Machine flexibility records	Workstation computers, sensors and monitoring equipment, Data collection terminals	Resource allocation and status module, database system, Data analytics tools, Maintenance management module	Jaskó et al. (2020)
	Efficiency (0–100%)	Adapting to machines with varying efficiency levels ensures LF adjusts to real-time performance, minimizing downtime and inefficiencies	Percentage (%)	Machine performance logs, Maintenance logs	Workstation computers, sensors and monitoring equipment, Energy consumption meters	Performance analysis module, Database system, Data analytics tools	Shojaeinasab et al. (2022)
	Standard working hours (Working pattern)	Maximizing machine utilization through labor availability across different shifts ensures LF reflects consistent capacity use throughout operating hours	Hours per day/week	Machine operation schedules, Log books	Workstation computers, Time tracking devices	Labor management module, Database system, Scheduling software	Chen et al. (2021)
Manpower	Main work center (skill)	Shifting laborers to tasks requiring specific skills ensures LF reflects optimal skill-resource allocation and addresses bottlenecks effectively	Numerical ratings	Skills assessment forms, Cross-training records, Job assignment logs	Workstation computers, Mobile devices	Labor management module, HR management system, Data analytics tools	Zwolińska et al. (2020)
	Alternative work centers (skill)*	Allocating the labor to alternative centers dynamically addresses changes in production demands, enabling LF to reflect adaptability	Numerical scale	Skills and cross-training records, Job assignment and rotation logs	Workstation computers, Mobile devices	Labor management module, Cross-training modules, HR management system, Data analytics tools	Mantravadi et al. (2023)

Table 6 (continued)

	Informational entity	Relation to LF	Units of measurement	Data source			References
				Manual system	Hardware	Software	
	Machine-man hour ratio	Efficient operation of machines reduces the man-hour requirement per machine, stabilizing LF by ensuring balanced labor-machine utilization	Man-hours per machine hour	Man-hour logs, Operation time sheets	Workstation computers, Time tracking devices	Resource allocation and status module, Database system, Data analytics tools	Peinl et al. (2023)
	Regular shift/working hours (experience)	Maintaining production across shifts with adaptable and experienced laborers ensures LF reflects steady labor availability and efficiency	Hours per shift/day	Employee timesheets, Schedule planners	Workstation computers, Time clocks or electronic time tracking systems	Labor management module, HR management system, Database system	Saenz de Ugarte et al. (2009)
	Overtime availability*	Flexibility in overtime availability ensures LF can accommodate unexpected workload spikes or urgent demands effectively	Hours available for overtime	Overtime availability logs, Overtime authorization records	Workstation computers, Time tracking systems	Labor management module, HR management system, Database system	Zwolińska et al. (2020)
Subcontract	Work center/operation*	Ensuring seamless integration of subcontracted tasks into the main production process allows LF to reflect the added capacity accurately	Numerical scale	Subcontractor task logs, Performance review form	Workstation computers, Mobile devices	Order management module, Database system, Data analytics tools, Contract management module	Da Costa Dias et al. (2021)

Table 6 (continued)

Informational entity	Relation to LF	Units of measurement	Data source			References
			Manual system	Hardware	Software	
Subcontractor*	Integrating subcontractor roles and assessing their performance ensures LF reflects their contribution to overall production efficiency	Numerical rating	Subcontractor Files, Performance evaluation forms	Workstation computers, Mobile devices	Order management module, Compliance management software, Database system, Data analytics tools	Chen et al. (2021)
Lead time*	Adapting to and compensating for subcontractor lead times ensures LF captures delays or extended timelines, enabling proactive adjustments	Time	Subcontractor project logs, milestone checklists	Workstation computers, Mobile devices	Scheduling and planning module, Database system, Data analytics tools	Jaskó et al. (2020)

*Data that are ‘nice-to-have’ for advance use of LF with contingent capacity management

Table 7 Performance-related informational entities

	Informational entity	Relation to LF	Units of measurement	Data source			References
				Manual system	Hardware	Software	
Job/Product related	Tardiness	Reducing production delays and meeting deadlines by reallocating labour ensures LF reflects real-time adjustments to meet performance goals	Time	Tardiness logs, Problem resolution records	Workstation computers, Mobile devices	Real-Time Analytics Software, Database System, Data Analytics Tools	Bianchini et al. (2024)
	Lateness	Adapting to changes in the production process minimizes lateness, ensuring LF dynamically accounts for variability and delays	Time	Lateness tracking logs, Delivery performance records	Workstation Computers, Mobile Devices	Data Collection and Acquisition Software, Database System, Data Analytics Tools	Jaskó et al. (2020)
	Strike rate*	Meeting diverse job requirements enhances strike rate, ensuring LF captures competitiveness and resource efficiency in managing customer demands	Percentage (%)	Quotation logs, Sales and customer feedback records	Workstation Computers, Mobile Devices	Order Management Module, Database System, Data Analytics Tools	Peinl et al. (2023)
	Production yield	Adapting to production requirements improves yield rates, ensuring LF reflects the balance between quality and operational efficiency	Percentage (%)	Quality control logs, Production batch records	Workstation Computers, Sensors and Data Loggers, Quality Control Equipment	Production Tracking Module, Database System, Data Analytics Tools	Shojaei-nasab et al. (2022)
Production process related	Work center throughput time*	Improving throughput by reallocating labor to bottlenecks ensures LF reflects optimized flow and resource allocation within work centers	Time	Work center logs, Problem tracking forms	Workstation Computers, Timers or Stopwatches, Sensors and Automated Tracking Systems	Performance Analysis Module, Database System, Data Analytics Tools	Chen et al. (2021)
	Shop-floor throughput time	Reducing shop-floor throughput time ensures LF reflects the efficiency of real-time labor adjustments to meet demand	Time	Shop-floor logs, parameter adjustment record	Workstation Computers, Time Tracking Systems	Production Tracking Module, Database System, Data Analytics Tools	Mantravadi et al. (2023)
	Manufacturing lead time	Reducing lead times ensures LF reflects proactive planning and labor availability for uninterrupted production flow	Time	Manufacturing scheduling logs, Parameter setting records	Workstation Computers, Mobile Devices	Scheduling and Planning Module, Database System, Data Analytics Tools	Saenz de Ugarte et al. (2009)

Table 7 (continued)

Informational entity	Relation to LF	Units of measurement	Data source			References
			Manual system	Hardware	Software	
Pool delay	Minimizing pool delays through rapid labor mobilization ensures LF dynamically addresses job queue inefficiencies	Time	Job processing logs, Parameter setting records	Workstation Computers, Mobile Devices	Order Management Module, Database System, Data Analytics Tools	Da Costa Dias et al. (2021)
Work-in-progress (WIP)*	Managing WIP levels dynamically ensures LF reflects bottleneck mitigation and smooth production flow	Number of jobs/tasks	WIP tracking logs, Production flow charts	Workstation Computers, Mobile Devices	Inventory Management Module, Database System, Data Analytics Tools	Jaskó et al. (2020)
Capacity utilization*	Enhancing capacity utilization ensures LF reflects optimal resource deployment to match production demands effectively	Percentage (%)	Capacity utilization logs, Efficiency tracking sheets	Workstation computers, Mobile devices	Resource allocation and status module, Database system, Data analytics tools	Zwolińska et al. (2020)

*Information that is ‘nice-to-have’ for advanced LF impacts or that needs to be gradually built up as the implementation progresses

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Declarations

Conflict of interest The authors reported no possible conflict of interest.

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