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Enhancing Labor Flexibility in Workload Control: The Development and Application of a Framework

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Abstract. This article delves into the integration of labor flexibility (LF) within Workload Control (WLC) in Make-to-Order (MTO) production settings. In a domain where existing literature offers limited guidance on data collection for optimizing LF, our study introduces the 'FlexiFlow' framework. This practical tool bridges this gap by enhancing operational efficiency and improving labor resource management and data acquisition in high-variety, low-volume MTO environments. We explore the interplay between WLC and LF through a systematic and narrative literature review. We explain effective data collection strategies, encompassing manual and digital methods, including Manufacturing Execution Systems (MES). The FlexiFlow framework, articulated through four detailed tables, equips companies with the tools to manage LF effectively, offering practical implications for practitioners. This framework extends theoretical understanding and offers actionable insights, significantly enhancing operational adaptability and efficiency. FlexiFlow improved production efficiency and responsiveness by reducing lead times and improving labor resource allocation.

Keywords: Workload Control · Labor Flexibility Implementation · Data Collection · Information Management

1 Introduction

Customization presents challenges and opportunities in the ever-changing manufacturing sector. MTO production processes require high customization and are growing due to customer preferences and competition [1–3]. This transition complicates demand prediction and due date setting. Failure to provide reliable due dates may harm long-term customer relationships and market position [4]. Thus, lead times and due-date predictions must be shortened and improved, especially in MTO. Profitability and on-time delivery depend on production planning and control (PPC) strategies [5, 6]. The PPC

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WLC method is designed for MTOs with many products but low production volumes [7, 8]. This method shows excellent improvement potential [9]. WLC improves MTO production efficiency by minimizing queuing times, reducing lead times, keeping lead times consistent with plans, meeting deadlines, maximizing work center utilization, and addressing the lead time syndrome [10–12]. To do so, WLC uses Input/Output Control (I/O/C) to balance production inputs and outputs, thereby optimizing the performance of manufacturing contexts [13, 14]. WLC input control (I/C) manages workflow by timing order releases, setting workload limits, prioritizing jobs, and adjusting input rates to match production capacity [15, 16]. In contrast, WLC Output Control (O/C) manages work outflow, adjusts capacities for efficient production, and maintains lead times [15, 16]. This study focuses on WLC O/C, mainly concentrating on a particular aspect: integrating LF in MTO companies to improve their operational efficiency.

LF helps flow shops adapt to demand changes and bottlenecks, improving production efficiency [17]. LF in O/C involves dynamically reallocating labor resources across tasks and stations to manage production output in workload-controlled environments. Cross-training, flexibility matrices, and worker assignment rules help create a flexible workforce that can adapt to demand changes and maintain production throughput [18]. WLC has been extensively studied in the extant scientific literature, but LF has not [15]. In particular, LF's incorporation into real-world WLC systems has been understudied [18]. Operational data shortages can make WLC implementation in real business scenarios difficult, but the literature rarely addresses this issue [2, 12]. Intelligent computer systems depend on data availability and are becoming more critical in WLC [15, 19]. Huang [20] identified information availability as a key challenge in WLC implementation, particularly in MTO. However, to the best of the authors' knowledge, this literature study does not focus on LF but instead touches on the general application of WLC in manufacturing firms.

Moreover, while this literature study offers guidance to companies on the necessary data for implementing WLC practically, it lacks clear indications on where to find this data (i.e., information sources) and how to measure it (i.e., units of measure to be adopted). Building on Huang's findings [20], this paper addresses the aforementioned gaps by providing a novel framework (herein called FlexiFlow), which will guide companies in understanding how to implement LF in real-world contexts. The proposed framework aims to outline the necessary data for implementing LF to analyze the information architecture within WLC and pinpoint the data sources, types, and units of measure pertinent to companies. This will streamline the practical tasks of data collection and, more generally, the application of LF in actual firms. Accordingly, the proposed framework will aim to answer the following Research Question (RQ): *How can real-world companies effectively implement WLC in LF?*

Lean flexibility is related to the conclusion regarding the implementation challenges and development of LF frameworks like FlexiFlow. Lean flexibility enhances an organization's adaptability and efficiency by streamlining processes, reducing waste, and improving response times through a more flexible workforce and operational methods [21]. The FlexiFlow framework aligns with these principles by offering a structured approach to effectively implementing LF. FlexiFlow analyzes WLC, units of measure, and data sources to optimize production processes, reflecting lean thinking's focus on efficiency and eliminating waste. Additionally, by defining the metrics and data sources needed for effective LF, FlexiFlow supports Lean's emphasis on realistic, data-driven decision-making to enhance operational responsiveness and reduce errors. This approach to continuous improvement is a core principle of lean management.

Moreover, FlexiFlow enhances the adaptability and responsiveness of manufacturing operations, which are key objectives of lean flexibility, by aiding in better workforce training and allocation based on refined data analysis. Integrating advanced technologies such as AI and IoT within the FlexiFlow framework could drive lean flexibility by enabling more dynamic and real-time adjustments to workforce allocation and process management [22]. Investigating FlexiFlow's adaptability to various industrial contexts with different operational demands can expand its utility, making it a more universally applicable tool in line with lean principles emphasizing versatility and waste reduction across different environments. Validating FlexiFlow through real-world case studies would provide practical evidence of its effectiveness, aligning with the lean principle of empirical validation of tools and processes. These connections underscore FlexiFlow's relevance to lean flexibility and suggest significant contributions it could make to advancing structured methodologies for incorporating LF in modern manufacturing.

This research aims to bridge the gap between LF theory and production management practice. We examine manual, hardware, and software data collection methods to propose practical strategies for companies to manage LF within the WLC framework. The paper has five sections below. Section 2 provides this study's theoretical foundation. Section 3 describes the FlexiFlow framework development process. Section 4 covers FlexiFlow and how it can improve LF in companies. Section 5 concludes with findings and research recommendations.

2 Theoretical Background

This study aims to provide a comprehensive framework to put LF (a particular aspect of WLC O/C) into practice in MTO. In this section, we give the theoretical groundwork that is essential for understanding the methodology and outcomes of this study before we get into those things. In Sect. 2.1, we define lean manufacturing; in Sect. 2.2, we cover WLC; in Sect. 2.3, we explore LF; in Sect. 2.4, we examine the applicability of WLC in practice.

2.1 Lean Manufacturing

Lean manufacturing, a transformative approach to production, emphasizes the elimination of waste to enhance efficiency and value. This methodology, deeply rooted in the Toyota Production System, aims to streamline operations by identifying and removing non-value-adding activities and optimizing resource use. Lean manufacturing focuses on continuous improvement and the relentless pursuit of waste elimination across seven categories: over-production, waiting, transportation, over-processing, inventory, motion, and defects. By addressing these areas, lean manufacturing seeks to deliver higher quality products, reduce costs, and shorten lead times, aligning production processes more closely with customer demands. The implementation of lean manufacturing principles has been shown to yield significant benefits across various sectors. Through case studies and simulations, researchers have demonstrated how lean strategies can improve operational efficiency, cost savings, and product quality. For instance, applying value stream mapping and lean tools such as Single Minute Exchange of Die and Cellular Manufacturing has effectively identified inefficiencies and optimized production flows. These methodologies enhance the manufacturing process and contribute to a more agile and responsive production system capable of precisely meeting customer needs [23, 24].

2.2 WLC

WLC is an essential tool in production management, particularly beneficial for companies with high-variety, low-volume production, such as those engaged in MTO [19]. WLC, known for efficiently managing queue levels in production, operates primarily through I/C and O/C. It has been recognized for significantly improving production system performance and aligning a shop's input rate with its output rate [13, 14]. I/C handles work entry, while O/C adjusts capacity to regulate work outflow. In recent studies, while WLC has been thoroughly explored, LF in WLC has not been given adequate attention [12]. This research focuses on how LF within WLC affects system performance. In high-variety, low-volume companies using WLC, it is vital to manage the timing of individual orders and maintain overall throughput. This study explores the relationship between due date setting, order release, and O/C and their combined effect on system performance [16, 25]. While due date setting and O/C address different performance aspects, order release is crucial for reducing work-in-process and boosting throughput, especially when making capacity adjustments is challenging.

2.3 Labor Flexibility

LF is the capacity of employees to acquire new skills and transition between various roles as needed. It is defined by the workforce's ability to handle various tasks within the manufacturing sector. This adaptability is evident in the ease of reallocating staff to different departments, a process facilitated by workers trained in multiple disciplines [26]. Such a versatile workforce is key in effectively managing design changes and introducing new products. Singh [27] emphasizes that increased LF significantly enhances the reassignment of duties, especially in the absence of regular staff members.

2.4 Applicability of LF in WLC

Common barriers to WLC application include a lack of complete and real-time information, industry awareness, end-user training, data availability, and complex material and information flows [28–30, 35]. From customer inquiry to MTO, WLC implementation is hindered by job information gaps [11]. The lack of historical data on job routing and processing times makes CE-stage estimates difficult [31, 32]. In MTO, shop-floor resources and job progress feedback are often inaccurate and incomplete. The trade-off between data granularity and error minimization is noted by Henrich et al. [33] and Hicks [34]. Silva, Roque, and Almeida [29] also noted that capacity unit workload norms, essential for effective WLC, remain unresolved.

In this context, Huang's pioneering work [20] answered the crucial question: What information is needed for successful WLC implementation? To the authors' knowledge, no other literature study has examined WLC implementation since Huang's groundbreaking work. Her work [20] helped establish a comprehensive information architecture for WLC implementation. Her study details WLC I/O/C and performance measurement data needs. This framework organizes information flow, which is crucial for implementing WLC in MTO due to data availability and management issues. Her work lacks two crucial indicators to assist companies in implementing WLC: the relations of the WLC in LF, where to locate the necessary WLC input information (source of data), and how to measure it. This research aims to extend and improve Huang's framework to fill these gaps in the following ways. We first define the relationship between WLC and LF; then, we state the units of measurement for each primary WLC data type. Lastly, we identify data sources, such as where and how to get WLC data. This includes finding digital and manual data collection methods for MTO operational contexts. We adapt Huang's information framework to support MTO companies in facing unique challenges and uncertainties when implementing WLC and, particularly, LF. Accordingly, we aim to provide a comprehensive framework that companies can leverage to implement LF and boost organizational productivity by strategically aligning information management with WLC principles.

3 Methodology

This section describes the methodology employed in conducting the study, illuminating the development of the FlexiFlow framework for implementing LF in MTO companies. To the best of the authors' knowledge, Huang's work [20] is the only WLC implementation framework available in the literature, and this work started by expanding on it. Huang's framework comprises four tables: I/C informational entities, practical perspectives of WLC I/C information, capacity-related information, and performance measurement entities. The first table (i.e., WLC I/C informational entities) outlines the data requirements for implementing WLC in manufacturing. WLC implementation issues and solutions are covered in the second table (i.e., practical perspectives of WLC I/C information. The third table (i.e., capacity-related information) analyzes machine and manpower data related to manufacturing capacity. Finally, the fourth table (i.e., performance measurement entities) covers WLC performance metrics like Tardiness and Production Yield.

Our research references these tables early in the text to provide a conceptual foundation for our readers. This is crucial for understanding how our FlexiFlow framework builds upon and diverges from Huang's original models. By discussing these tables at the beginning, we ensure that readers can follow the logical progression of our study as we expand on Huang's framework to integrate LF within WLC. To ensure clarity and coherence, the referenced tables from Huang's work are detailed upfront, allowing us to systematically explain their relevance and how they inform the development of FlexiFlow. This structured approach aids in comprehending the subsequent discussions and analyses that lead to the creation of our new framework.

Huang's comprehensive framework lacks specificity in WLC's relationship with LF. Moreover, this literature framework does not clarify the units of measurement and data sources, which are crucial for dynamic MTO application. Indeed, knowing data sources affects WLC data reliability and relevance, affecting decision quality. Here, Huang's original tables' structural integrity is combined with missing data to fill critical gaps. The missing data are gathered by developing a literature review as follows.

We conducted a preliminary literature review to determine WLC's relationship to LF, units of measurement, and data sources and provide MTO with a framework to apply LF. We explored Scopus and grey literature in a narrative literature review. We ended our preliminary review with the following main points. Our methodology emphasizes the role of Manufacturing Execution Systems (MES) in helping MTO companies implement LF within WLC frameworks. MES are specifically considered because they are crucial to smart manufacturing operational efficiency in MTOs. MES can track shop floor activity, machine performance, and real-time production progress. These systems facilitate the collection of accurate, real-time data necessary for scheduling production and managing workloads in dynamic MTO environments. MES integration ensures data accuracy and timeliness, which is essential for implementing LF strategies and effective WLC. Given their importance in operational efficiency and flexibility, our research examines how best to utilize MES to support WLC and LF. This focus is justified by the need to address a significant gap in the literature regarding how data collection and management impact WLC outcomes in MTO settings. We aim to provide a detailed, practical framework for companies to leverage MES to improve decision-making and operational adaptability.

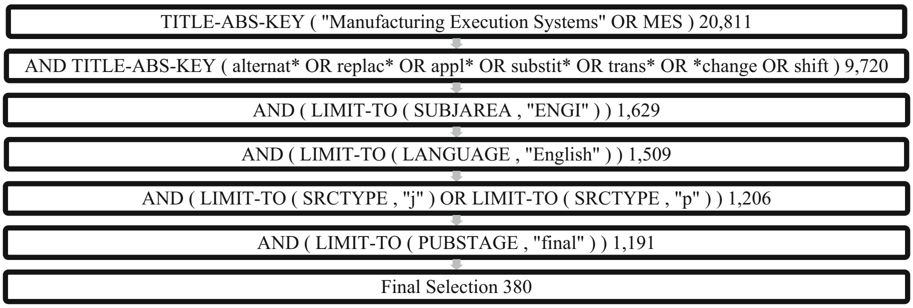

Fig. 1. Paper screening process.

First, a systematic literature review was performed by consulting Scopus with the search query and methodology summarized in Fig. 1. Scopus searched for studies on "Manufacturing Execution Systems". The search yielded 20,811 publications. Our search was refined by adding MES application and manufacturing process adaptation terms. Narrowing the results showed MES's flexibility. Limiting the subject to "Engineering" narrowed the sources for MES manufacturing engineering and technology. For global relevance, we reviewed English-language studies. We used peer-reviewed journal articles ("j" in Fig. 1) and conference papers ("p"). To ensure peer review, "final" publications were reviewed. The final selection involved consulting the titles and abstracts of papers, filtering those significant for our research (i.e., articles that examine how digitalization affects WLC practices) while excluding the other papers. Thanks to this thorough process, 380 relevant and high-quality literature were found that explained

MES integration in WLC practices. An in-depth analysis of the selected literature was performed by reading the full text of the papers. This consultation determined the data and unit of measure MES can use to record and manage WLC implementation with LF.

In addition, grey literature was consulted to complement the systematic review with a narrative review. The narrative review broadened the research's analytical scope. It included many perspectives, especially on manual procedures for collecting and measuring data (which are underrepresented in Scopus compared to MES). Industry reports, service provider platform insights, and specialized forum discussions explain manual measurement systems and their industry applications. This method deepens the literature review and reduces publication bias, giving a more balanced and inclusive view of high-tech and manual data collection [36]. The narrative review used clear selection criteria and multiple sources to ensure objectivity. The authors chose narrative review sources that considered the central theme of WLC implementation in MTO. With this, WLC data needs are clear. Each source was carefully assessed, prioritizing manufacturing and workload management articles and industry reports. We deliberately used diverse sources to show different perspectives. We learned about WLC implementation in various manufacturing contexts using this method. We valued case studies and real-world applications to ground the findings. These diverse findings from the systematic and narrative literature review were integrated into the final FlexiFlow framework, thus presenting a holistic view of MTO LF within WLC.

4 Results

An effective WLC requires complete job information. This includes job quantity, operational sequences, set-up and processing times, and production stages. Understanding manufacturing capacity, material supply, and customer details enhances this data. Consulting through our FlexiFlow (Fig. 2) helps businesses navigate and consolidate WLC-related information, mainly focusing on the information needed to implement LF. Our framework was built based on Huang's four comprehensive tables (already described in Sect. 3). However, we have expanded Huang's work by adding two columns to each table: units of measurement and data sources, using the scientific and grey literature retrieved through the review mentioned in the previous section. The achieved framework is depicted in Fig. 2. FlexiFlow emphasizes the need for detailed job information, appropriate units of measurement, and data sources when implementing LF in WLC.

With precise units of measurement and reliable data sources, companies can improve data-driven decision-making, reducing waste, lead times, and resource utilization and boosting profitability. FlexiFlow improves operational efficiency, customer service, workload forecasting, capacity planning, and resource allocation. Its data sources and units of measurement may benefit WLC in two ways. It reduces data collection and analysis errors, improving WLC results. Second, depending on company digitization, FlexiFlow customizes units of measurement and data sources for seamless integration with manual or technological (hardware and software, MES) record-keeping systems. Companies with varying technological capabilities should collect data manually if MES is unavailable. Digital systems like MES standardize and integrate manual data. Thus, this new framework allows firms to implement LF in different contexts without replacing their data systems.

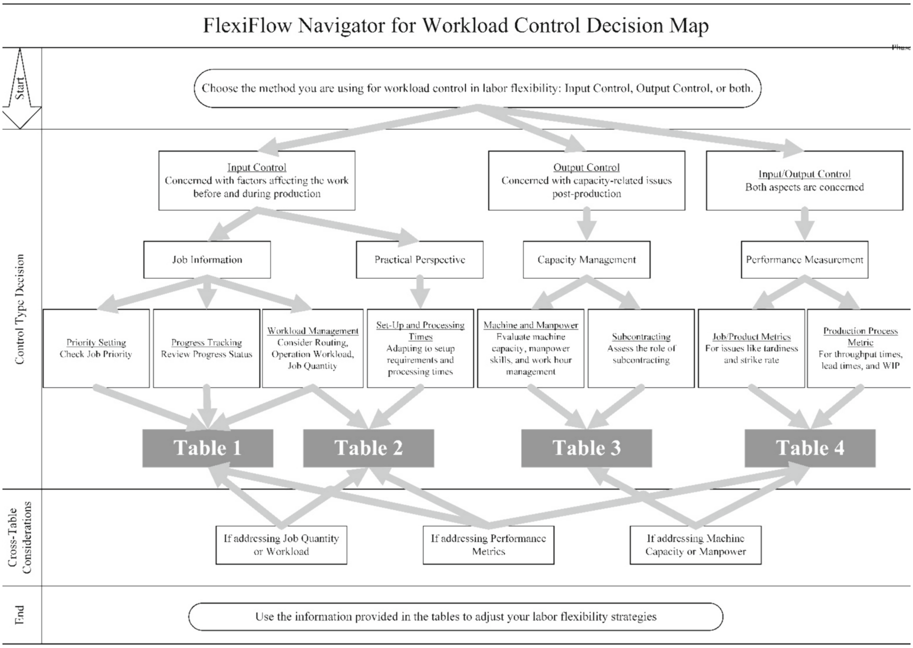

Fig. 2. FlexiFlow is a framework for supporting companies in implementing LF.

The FlexiFlow facilitates LF strategy adjustments by addressing WLC. The practitioner has to start at Fig. 2 and choose the control focus I/O/C that best suits his goal of using it. Choose an operation element to manage, such as Job Information, Practical Perspective, Capacity Management, or Performance Measurement. Choose an element and find a sub-element like Priority Setting or Machine and Manpower that needs attention. After that, consult Tables 1, 2, 3, or 4 for task data and criteria. Remember that a complete understanding may require consulting multiple tables to access all relevant data, such as Performance Metrics in Tables 1, 2, and 4. The flowchart's "Cross-Table Considerations" section encourages a holistic approach by combining data from multiple tables to form a solid analysis and strategy. This integrated approach considers all aspects of LF, making WLC more effective and efficient.

With consulting FlexiFlow, Table 1 shows that MTO, where each product has unique set-up times, needs WLC I/C recording and analysis to prevent idleness and control worker movements.

LF is essential for managing production and meeting changing demands in dynamic manufacturing. Several factors affect LF, including skilled worker allocation, workload management, and operation scheduling. These factors are listed in the tables below.

Regarding improving WLC in LF, Table 2 shows digital and manual methods to track job quantities, set-up times, and operation completions to improve production precision and efficiency.

FlexiFlow shows that Table 3 can be used in several real-world examples to monitor and manage machine efficiency, workforce skills, and subcontractor performance to

Table 1. WLC I/C informational entities

Factor	Relation to LF	Units of Measurement	Data Sources		
			Manual System	Hardware	Software
Routing (Estimated)	Allocating skilled workers to different work centers as per job requirements	Units Produced/Capacity Units	Routing Sheets, Workload Logs	Workstation Computers (WC), Network Infrastructure (NI), Database System (DS)	Scheduling and Planning Module (SPM), API, Data Analytics Tools (DAT)
Operation Workload (Estimated)					
Setup Time	Reducing setup time by adapting to different machines/processes quickly	Time	Setup Time Logs, Event-Driven Checklists	WC, Timers or Stopwatches (TS), Mobile Devices (MD)	Maintenance Management Module (MMM), DS, DAT
Processing Time	Managing varying processing times by reallocating workers based on demands	Time/Unit	Operation Time Logs, Batch Records	WC, Sensors and Data Loggers (SDL), TS	Performance Analysis Module (PAM), DS, DAT
Job Quantity (Produced Items)	Adjusting workforce in response to changes in job quantity	Number of units	Job Order Logs, Production Scheduling Boards	WC, Barcode Scanners (BS)	Order Management Module (OMM), DS, DAT
Progress Status (Actual)					
Enquiry Date	Ensuring availability of skilled workers for new jobs	Date	Enquiry Logs, Customer Interaction Records,	WC, Enquiry Panel	OMM, DS, DAT
Confirmation Date	Mobilizing the workforce quickly after job confirmation	Date	Confirmation Log Books, Digital Spreadsheets	WC, Scanners, Data Entry Devices	OMM, DS, DAT
Material Arrival Date	Efficiently assigning workers as materials arrive	Date	Material Arrival Logs, Inventory Spreadsheets	WC, BS, MD	Inventory Management Module (IMM), DS, DAT
Contractual Due Date	Meeting due dates through dynamic labor reallocation	Date	Contract Files, Due Date Calendars, Schedule Boards	WC, Document Scanners	SPM, Contract Management Module (CMM), DS, DAT
Job Release Date	Starting jobs promptly upon release	Date	Job Release Logs, Production Scheduling Boards	WC, BS, RFID Readers	IMM, DS, DAT
Completion Time	Meeting or optimizing operation completion times by adjusting labor resources	Date	Operation Completion Log, Time Sheets	WC, Clocks or Timers (CT), SDL	Production Tracking Module (PTM), DS, DAT

(*continued*)

Table 1. (*continued*)

Factor	Relation to LF	Units of Measurement	Data Sources		
			Manual System	Hardware	Software
Delivery Date	Meeting delivery dates through efficient production	Date	Delivery Logs, Delivery Confirmation Records	WC, GPS Trackers, Delivery Scanners, MD	OMM, DS, DAT
Priority Setting					
Job Priority (Estimated)	Allocating the right amount and skill set of labor based on job priority	Level (Normal/High)	Priority Setting Protocols, Job Tracking Spreadsheets, Visual Scheduling Boards	WC, NI, DS	OMM, Rules-Based System, DS, DAT

Table 2. A practical perspective of WLC I/C information

Factor	Relation to LF	Units of Measurement	Data Source		
			Manual System	Hardware	Software
Job Quantity	Reallocating workers to handle unexpected increases in job quantity	Number of units	Production Logs, Batch Records	WC, BS, Scales or Counting Devices	OMM, DS, DAT, Quality Control Software
Operation Setup Times	Adapting quickly to different setup requirements and transitioning efficiently	Time	Setup Logs, Time Recording Sheets	WC, TS	MMM, DS, DAT
Operation Processing Times	Dynamically allocating labor based on actual processing times	Days or hours per operation	Operation Time Logs, Expert Estimation Records	WC, TS, SDL	PAM, DS, DAT
Operation Completion Time	Enabling quick responses to changes or delays in operation completion	Time or Date	Manual Time Logs, End-of-Operation Checklists, Timestamps on Operational Documents	WC, CT	PTM, DS, Basic Digital Tools

ensure timely order completion, optimized machine utilization, and effective manpower allocation.

Finally, FlexiFlow shows that Table 4 can track and analyze job tardiness, production yield, and capacity utilization in MTO scenarios. Improved customer satisfaction, cost-effectiveness, and resource allocation help companies improve production efficiency and decision-making.

Tables 1, 2, 3 and 4 demonstrate how FlexiFlow's units of measurement and data sources can be used in different manufacturing scenarios with different data collection

Table 3. Capacity-related informational entities

Factor	Relation to LF	Units of Measurement	Data Source		
			Manual System	Hardware	Software
Machine Capacity					
Work center (operation function)	Ensuring workers are skilled in operating different machines or adapting to various operational functions	Units Produced/Capacity Units	Machine Operation Logs, Machine Efficiency Checklists, Machine Flexibility Records	WC, Sensors and Monitoring Equipment (SAME), Data Collection Terminals	Resource Allocation and Status Module (RASM), DS, DAT, MMM
Efficiency (0–100%)	Adapting to machines with varying efficiency levels	Percentage (%)	Machine Performance Logs, Maintenance Logs	WC, SAME, Energy Consumption Meters	PAM, DS, DAT
Standard working hours (working pattern)	Maximizing machine utilization by having skilled workers available across different shifts	Hours per day/week	Machine Operation Schedules, Log Books	WC, Time Tracking Devices (TTD)	Labor Management Module (LMM), DS, Scheduling Software
Manpower					
Main work center (skill)	Shifting workers to different tasks based on skill requirements	Numerical Ratings	Skills Assessment Forms, Cross-Training Records, Job Assignment Logs	WC, MD	LMM, HR Management System (HRMS), DAT
Alternative work centers (skill)	Allocating workforce adaptably, especially in response to changing production demands	Numerical Scale	Skills and Cross-Training Records, Job Assignment and Rotation Logs	WC, MD	LMM, Cross-Training Modules, HRMS, DAT
Machine-man hour ratio	Operating machines more efficiently, potentially reducing man-hours required	Man-hours per machine hour	Man-Hour Logs, Operation Time Sheets	WC, TTD	RASM, DS, DAT

(continued)

Table 3. (*continued*)

Factor	Relation to LF	Units of Measurement	Data Source		
			Manual System	Hardware	Software
Regular shift/working hours (experience)	Maintaining production efficiently across various shifts through shift adaptability and experience	Hours per shift/day	Employee Timesheets, Schedule Planners	WC, Time Clocks or Electronic Time Tracking Systems (TTS)	LMM, HRMS, DS
Overtime availability	Meeting unexpected demands or deadlines through flexibility in overtime availability	Hours available for overtime	Overtime Availability Logs, Overtime Authorization Records	WC, TTS	LMM, HRMS, DS
Subcontract					
Work/center operation	Ensuring seamless integration of subcontracted tasks into the main production process	Numerical Scale	Subcontractor Task Logs, Performance Review Form	WC, MD	OMM, DS, DAT, CMM
Subcontractor	Adapting to and integrating subcontractor roles to impact overall production efficiency	Numerical Rating	Subcontractor Files, Performance Evaluation Forms	WC, MD	OMM, Compliance Management Software, DS, DAT
Lead time	Adapting to and compensating for lead times associated with subcontracted work	Time	Subcontractor Project Logs, Milestone Checklists	WC, MD	SPM, DS, DAT

automation (using digital or manual tools). FlexiFlow addresses RQ and helps companies implement LF in real-world business settings by explaining input data, units of measure, and sourcing options. Integrating correct data management systems boosts the accuracy and efficiency of MTO companies.

In optimizing 'machine and manpower,' particularly focusing on controlling manpower skills, applying the FlexiFlow framework provides a structured methodology. Here is an example case study on how such a company should navigate FlexiFlow: In this case study, a company seeking to optimize 'machine and manpower' with an emphasis on controlling manpower skills would engage with the framework as follows: Initially, the company examines Fig. 2. Within FlexiFlow to determine the appropriate control focus for their needs, which in this scenario, directs them towards O/C, pertinent to post-production capacities. Once following the O/C path, 'Capacity Management' is pinpointed as the essential element that matches the company's objective to enhance manpower efficiency. Subsequently, the focus is narrowed down to the 'Machine and

Table 4. WLC performance measurement entities

Factor	Relation to LF	Units of Measurement	Data Source		
			Manual System	Hardware	Software
Job/Product Related					
Tardiness	Reducing production delays and meeting deadlines by reallocating labor quickly	Time	Tardiness Logs, Problem Resolution Records	WC, MD	Real-Time Analytics Software, DS, DAT
Lateness	Adapting to changes or issues in the production process, potentially reducing average lateness	Time	Lateness Tracking Logs, Delivery Performance Records	WC, MD	Data Collection and Acquisition Software, DS, DAT
Strike Rate	Enhancing competitiveness by meeting diverse job requirements, influencing the strike rate	Percentage (%)	Quotation Logs, Sales and Customer Feedback Records	WC, MD	OMM, DS, DAT
Production Yield	Adapting quickly to different production requirements, improving yield rates	Percentage (%)	Quality Control Logs, Production Batch Records	WC, SDL, Quality Control Equipment	PTM, DS, DAT
Production Process Related					
Work Center Throughput Time	Improving throughput time by reallocating labor to bottlenecks or high-demand areas	Time	Work Center Logs, Problem Tracking Forms	WC, TS, Sensors and Automated Tracking Systems	PAM, DS, DAT

(*continued*)

Table 4. *(continued)*

Factor	Relation to LF	Units of Measurement	Data Source		
			Manual System	Hardware	Software
Shop-floor Throughput Time	Reducing shop-floor throughput time through dynamic workforce adjustments	Time	Shop-Floor Logs, Parameter Adjustment Record	WC, TTS	PTM, DS, DAT
Manufacturing Lead Time	Reducing lead times by ensuring skilled workers are available when needed	Time	Manufacturing Scheduling Logs, Parameter Setting Records	WC, MD	SPM, DS, DAT
Pool Delay	Mobilizing the workforce quickly to reduce pool delays	Time	Job Processing Logs, Parameter Setting Records	WC, MD	OMM, DS, DAT
Work-in-Progress (WIP)	Managing WIP levels by adjusting labor allocation based on production flow and bottlenecks	Number of jobs/tasks	WIP Tracking Logs, Production Flow Charts	WC, MD	IMM, DS, DAT
Capacity Utilization	Enhancing capacity utilization by effectively deploying the workforce to match capacity needs	Percentage (%)	Capacity Utilization Logs, Efficiency Tracking Sheets,	WC, MD	RASM, DS, DAT

Manpower' sub-element, underscoring a combined interest in optimizing both human and mechanical resources.

With this aim in mind, the company consults Table 3 of the FlexiFlow framework, which should provide relevant data. They expect to find comprehensive criteria for evaluating manpower skills, guidelines for aligning them with production requirements, strategies for effective manpower capacity planning, and insights into machine efficiency and manpower skills. Using Table 3, the company can create and implement a strategy to improve manpower skills through structured training, strategic hiring, or organizational adjustments. The data would also inform machinery operation, maintenance schedules, and production workflow to improve operational efficiency and capacity. Thus, the FlexiFlow framework allows companies to collect, analyze, and apply data to optimize machine and manpower operations.

5 Conclusion

The lack of data collection and use instructions makes implementing LF in real companies difficult. This research used a preliminary literature study [20] and systematic and narrative literature to develop FlexiFlow, a four-table framework to help companies implement LF. This new framework analyzes WLC, units of measure, and data sources to optimize production processes. This study bridges theory and practice in WLC implementation. It helps MTO understand the data needed to implement LF, its sources (manual and technological), and the best unit of measure. FlexiFlow simplifies MTO data management and acquisition for LF by defining metrics and origins for each data type and preventing retrieval and analysis errors. This advancement helps companies navigate WLC, providing insights on workforce training, allocation, data refinement, and analysis to improve production efficiency and responsiveness.

FlexiFlow is comprehensive in developing an LF guide, but it has limitations. Due to its theoretical strengths, the framework needs real-world case studies to prove its practicality. Its adaptability to other industries with different operational demands and technological advancements is unclear because it is designed for MTO. FlexiFlow lacks AI and IoT integration, which modern manufacturing requires. Multitasking and digitalization in manufacturing are also ignored. Industry-specific technology development makes the framework less applicable. Best-practice data sources should be updated as market and technological capabilities change. This flexibility keeps the framework relevant and effective as technology and market demands change. Creating a manufacturing LF framework is our priority. Companies will be contacted to help them implement the framework. Finally, the new framework may improve operational efficiency and adaptability in industrial manufacturing and other settings, but more research is needed.

Future research could validate FlexiFlow by showing its application to real-world case studies. Moreover, its applicability could be assessed across industries with differing technological development. Here, the effects of digital technologies on manufacturing (especially multitasking jobs) could be studied. Finally, additional studies could investigate how FlexiFlow can integrate AI and IoT to improve operational efficiency and adaptability in diverse manufacturing settings. These research directions would corroborate and improve FlexiFlow, stimulating its use in industrial manufacturing.

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