# Challenges in Developing Digital Twins for Labor-Intensive Manufacturing Systems: A Step towards Human-centricity

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# Challenges in Developing Digital Twins for Labor-Intensive Manufacturing Systems: A Step towards Human-centricity

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**Abstract**

Many existing manufacturing systems still rely heavily on human workers as the backbone of their production processes. Such systems are commonly termed labor-intensive. Developing Digital Twins for labor-intensive manufacturing lines is a complex and challenging task as human involvement adds another level of uncertainty. While Digital Twins offer numerous benefits, such as improved efficiency, reduced downtime, and enhanced decision-making, they also come with unique challenges when they need to be developed for labor-intensive manufacturing systems. In this paper, we discuss the main challenges and their implications that arise from existing research. Considering these challenges, we propose a framework for developing data-driven Digital Twins of labor-intensive manufacturing systems as an initial step towards addressing these challenges. We illustrate the challenges associated with Digital Twins of labor-intensive manufacturing systems through a practical case study derived from our collaboration with two companies. In the case study, we make necessary preparations for developing Digital Twins for decision support in job scheduling in a hybrid machine-worker environment while considering the well-being of workers.



*Keywords:* Digital Twins; labor-intensive Manufacturing; human-centric Manufacturing; Data-driven Simulation; Modeling and Simulation

## 1. Introduction

In the current industrial landscape, manufacturing systems face challenges that have significant implications for productivity, efficiency, and overall performance. The growing complexity of these systems and the need for optimization, efficient resource allocation, and adaptability demands innovative approaches [1]. One solution that has gained prominence is Digital Twins (DTs), which are digital replicas of real-world manufacturing systems that continuously update with the changes in the manufacturing systems. DTs enable methods like predictive maintenance and simulation-based optimization. Consequently, companies have a strong motivation to develop DTs for their manufacturing systems [2].

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In addition, particularly in recent years, companies have increasingly acknowledged the importance of flexible production options that are capable of adjusting quickly to new circumstances. In the context of labor-intensive manufacturing systems (LIMSs), where workers are the most adaptable elements within the cyber-physical production system, it becomes essential to maximize their potential. In a novel move towards human-centric manufacturing (HCM), the primary objective is to leverage the unique strengths of human workers, such as creativity, problem-solving, as well as adaptability, and integrating them with advanced technologies. The aim is to create a production environment that optimally combines human expertise and technological capabilities, resulting in improved productivity, quality, and agility [3].

To achieve this shift towards HCM, it is imperative to provide technological support that allows workers to take on the roles of flexible problem-solvers and decision-makers [4]. One key enabler in the transformation towards HCM is the development of DTs that can accurately capture and model human operators. We envision DTs for LIMSs as digital representations of not only the physical manufacturing systems but also the human operators within these systems. These advanced DTs would provide a more comprehensive view of the manufacturing processes by also capturing the complex interactions between humans and machines. Such DTs would enable manufacturing companies to optimize processes while considering the impact of human factors, such as motivation, fatigue, and emotional state. In this way, more informed decision-making and efficient resource allocation can be facilitated, ultimately increasing workers' well-being, productivity, and product quality simultaneously in a multi-objective manner.

The remainder of the paper is structured as follows: Section 2 provides background information on DTs and their role in the transition to HCM systems. Section 3 outlines the derived challenges in creating DTs for LIMSs. In Section 4, we propose a framework to address these challenges. Section 5 illustrates the framework through a case study, followed by a summary and outlook in Section 6.

## 2. Background and Related Work

In the following, we establish the context for the remainder of the paper by introducing DTs and HCM lines, as well as providing an overview of the related literature.

### *2.1. Digital Twins*

Over the years, since the term DT was introduced in the early 2000s, several definitions emerged. Söderberg et al. describe a DT as a thorough physical and functional description of a component, product, or system that contains almost all of the information that might be helpful during the present and later stages of the product's lifespan. [5]. Michael Grieves, who established the term DT, described a DT as a collection of virtual information constructs that completely characterizes a potential or real physical manufactured product from the micro-atomic to the macro-geometrical levels [6]. Friederich et al. define DTs as dynamic simulation models of archived and present behaviors of physical objects or processes that help optimize relevant performance metrics [7].

Michael Grieves initially defined three main components of a DT: the physical space and its products, the virtual or digital space, and its products, as well as the connection between the two spaces. Throughout the years, in his perspective, these elements have undergone minimal changes [8]. Friederich et al. establish the following elements: a real-world entity, a data-driven simulation model comprised of algorithms to describe the simulation model and connectivity components as well as data from the real-world entity [7]. In our work, we refer to the definitions by Friederich et al. In the following, we describe the key components of a DT, including the simulation model, data integration, and the communication pipeline.

**Simulation Model:** Simulation models are computational representations of real-world systems or processes which emulate the behavior of the corresponding systems over time, providing digital environments to analyze and understand systems' dynamics. Both traditional simulation models and DTs are designed for predefined objectives. These objectives might involve improving key performance indicators, such as productivity or workers' well-being, optimizing the layout of the shop floor, or identifying bottlenecks in the production processes. The resulting DTs can be seen as projections of the real world entity on predefined objectives, resulting in digital replicas derived from relevant sensor data, information, and knowledge. Consequently, the digital replicas only capture characteristics of the real-world entity that are highly relevant to the overarching goal. By focusing on these highly goal-relevant characteristics, the resulting DT ideally should be lean, characterized by minimal computational complexity, and unobstructed exploration of simulation "what-if" scenarios.

In the past, traditional simulation models have been tailor-made for specific manufacturing systems in a manual, labor-intensive way. This traditional approach leads to resulting models being quickly outdated, especially in modern manufacturing systems that feature frequent adjustments, necessary due to evolving demands. Thus, data-driven DTs try to circumvent this challenge by leveraging data and techniques, such as process mining or machine learning, to extract models and their parameters [7]. In Section 4 we present our approach to extract data-driven DT for LIMSs.

**Data Integration:** The (near-)real-time data integration is critical for maintaining the fidelity of the DT [9]. The system continuously collects data from sensors, IoT devices, and other sources installed in the real-world entity. This real-world data helps update and synchronize the simulation model with the current state of the physical system. Furthermore, (near-)real-time data integration combined with a data storage architecture enables historical data storage, providing a rich archive of past states and performance metrics. This historical context is invaluable for trend analysis, long-term performance evaluation, and retrospective decision-making that can be valuable to DTs' decision support capabilities.

**Communication Pipeline:** DTs can communicate with their real-world counterparts, enabling bidirectional information exchange. This feature is particularly valuable in cases where adjustments or control actions are needed in response to changing conditions [9]. This intra-twin communication encompasses two key elements: raw data transmission and processed information transmission. Raw data, originating from sensors within the real-world entity, flows into the DTs, while processed information and actionable insights, generated within the DTs, are sent back to the real-world entity.

In conclusion, DTs can be seen as a natural evolution of traditional simulation models in the sense that they are the automated and data-driven way to use the principles of modeling and simulation.

### 2.2. *From Labor-Intensive to Human-centric Manufacturing Systems*

Over the decades, companies have consistently strived to increase the efficiency, reliability, and productivity of their manufacturing processes. One common approach in traditional manufacturing systems to achieve these goals is automation. These systems prioritize efficiency, cost reduction, and increased throughput by mechanizing and digitizing tasks, thus minimizing human intervention. Key features of classical manufacturing include the introduction of assembly lines, just-in-time production, and advanced robotics, which have streamlined processes and facilitated large-scale production of standardized products.

Despite the success of automation, there are several areas in which automation is not yet feasible or cost-effective due to the complexity of tasks, the inability to fully automate certain processes, or the need for human skills and judgment. These challenges are particularly pronounced in LIMSs, such as apparel, footwear, home goods, and textiles, where most of the operations are performed by human workers [10].

In our research, we aim to bridge the gap between classical manufacturing and HCM. Through the creation of DTs for LIMSs, we are taking a first step towards HCM. This approach allows us to leverage the cognitive and problem-solving capabilities of human workers, enhancing the capabilities of automation. Ultimately, HCM strives to integrate the advantages of automation with the creativity and adaptability inherent in the human workforce, fostering a more sustainable and flexible manufacturing ecosystem.

### 2.3. *Simulation and Digital Twins for Labor-Intensive Manufacturing*

To position our study in a broader context, in the following, we provide an overview of existing related research, summarized in Table 1. We also highlight the challenges that have been derived by insights from these papers, which are described in-depth in Section 3. Literature on LIMSs utilizing DTs is notably limited. Even when expanding the scope to simulation rather than DTs, a significant research gap persists. We selected papers that describe practical applications of data-driven methods combined with simulation techniques, aiming to optimize and enhance specific aspects within LIMSs. We favored these practical applications over theoretical work because they offer real-world relevance and concretely point to challenges encountered by researchers and companies. These challenges, along with other factors such as lessons learned, informed the development of our proposed framework. Moreover, the existing literature body on applying traditional simulation in LIMSs serves as a valuable resource for knowledge transfer toward DTs.

In a recent related effort, Aslan et al. [11] sought to optimize worker allocation using positional data in a simulation model. Results showed a 7% reduction in completion time, rising to 16% with additional workers addressing bottlenecks. This work showcased the challenges of dynamic systems, capturing human operations, and data privacy. In another LIMS-focused study, Ferjani et al. [12] aimed to create a simulation model incorporating fatigue for evaluating the effects of production scenarios on system performance and workers. However, as the fatigue prediction involves personal data, the study raises challenges related to capturing human operations and ensuring data privacy. In an earlier effort, in 2005, Lassila et al. [13] aimed to identify bottlenecks within a LIMS. To achieve this, the authors explicitly modeled human workers as processes with limited capacity and scheduled availability. The model revealed that the majority of a product's lead time was spent in buffers between operations. This study pointed out challenges with dynamic manufacturing systems as the case study LIMS had two products with different procedures. The study, furthermore, showcased challenges related to capturing human operations and data availability as the approach used processing times of each worker. Around the same time, Baines et al. [14] tried to improve the prediction accuracy of LIMSs' simulation models by incorporating human factors into the models, since most models overpredict productivity. The overprediction occurs due to neglecting human elements like fatigue that directly impact productivity. In their approach, they incorporated a circadian rhythm and an aging-related model. With that inclusion, the cycle times increased by up to 35% and, thus, resemble the actual cycle times more closely. However, the validation proved to be complicated, as the models required personal data. This research points out multiple challenges related to tracking and availability of necessary data points and concerns for data privacy. The aim of Baskaran et al. [15] was to analyze ergonomics in an automotive assembly process. Therefore, they simulated humans within a human DT based on biomechanical, anthropometric, and ergonomic characteristics tables. To use this model on a broader scale, the challenges of data privacy and availability, as well as capturing human operations, need to be addressed which was not the case in the presented effort. Fantini et al. [16] introduce a framework to enhance the analysis of human work in cyber-physical production systems and emphasize the potential and challenges of human integration. They use a human component that is defined by the required skillset for specific tasks. This raises questions about automated skillset capture and adaptation to evolving systems, while also prompting concerns about data privacy due to the close monitoring required for each worker's skillset progression.

The reviewed works show the complexity of modeling and simulation of LIMSs and pointed out a number of challenges that we detail in the following section.

| Study | Objective | Simulation Paradigm | Influenced Challenges |
|---|---|---|---|
| [11] | Worker Capacity Allocation | Discrete Event Simulation | C1, C2, C4 |
| [12] | Modeling Workers Fatigue for Decision Support | System Dynamics, Agent-based Simulation, Discrete Event Simulation | C2, C4 |
| [13] | Bottleneck Identification | Discrete Event Simulation | C1, C2, C4 |
| [14] | Improve Simulation Accuracy and Reliability with Human Factors | Discrete Event Simulation | C2, C3, C4 |
| [15] | Analyze Ergonomic Impact | Discrete Event Simulation | C1, C3, C4 |
| [16] | Enhance design and assessment of human work | Discrete Event Simulation | C1, C2, C4 |

Table 1. Summary of related practical studies and their impact on the derived challenges.

## 3. Challenges in Creating Digital Twins for Labor-intensive Manufacturing Systems

As a result of our literature research through the available practical studies, we extracted four key challenges in creating DTs of LIMSs, which we elaborate on in the following.

**C1: Dynamic Manufacturing Systems:** Manufacturing systems are often dynamic, with processes and tasks that can change rapidly based on demand or other factors. This dynamic nature is further amplified in LIMSs, particularly through human involvement, introducing an additional layer of uncertainty. For instance, human operators in LIMSs may lead to variations in task execution, potential errors, and unpredictable response times. These variations lead to a continuous evolution of data, driven by adaptations or updates to manufacturing processes or machines. Creating DTs that can adapt to these changes in (near-)real-time is a considerable challenge. These DTs and their underlying models must adjust as quickly as possible to new circumstances while being resistant to noise, which can be introduced through various factors such as malfunctioning sensors, transmission complications, or human errors.

**C2: Capturing Human Operations:** Tracking relevant data points of workers' operations has two major challenges. Firstly, appropriate sensors need to be researched and installed that can track the needed data and do not interfere with the processes. These sensors should also be flexible enough to be adapted in the future if the process or scenario changes, while also complying with the data privacy legislation [17, 18]. Secondly, workers, generally, even though adhering to a protocol or process are not programmed machines in that they do not execute the same step identically all the time. This is intensified by the fluctuation of factors like motivation, well-being, and energy levels. Currently, humans are often modeled as pseudo-technological elements; however, in reality, human behavior is quite different [14]. As a result, additional uncertainty is introduced in the system, which needs to be accurately modeled and accounted for [19].

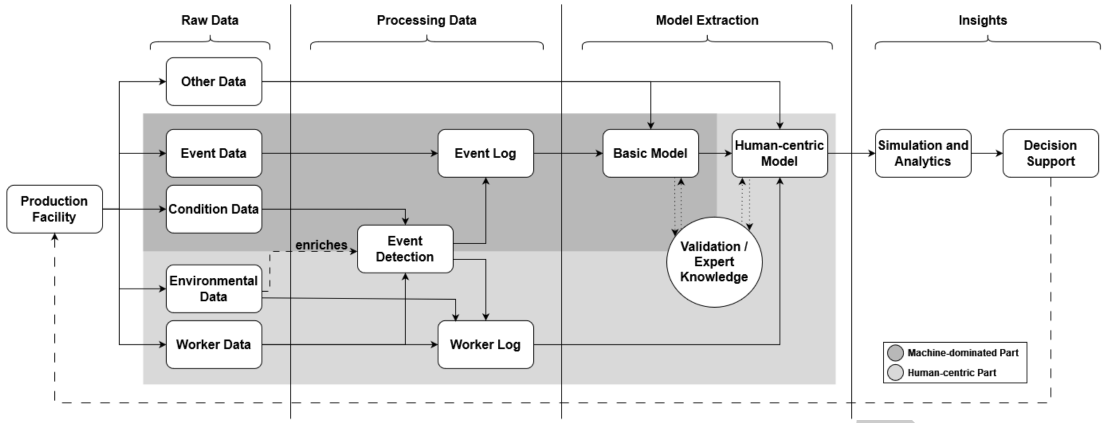


Fig. 1. Framework for creation of Digital Twins for labor-intensive manufacturing systems.



**C3: Data Availability:** Most companies nowadays track and store data of their production. While a company may deploy sensors to collect workers' data, compliance with modern data and worker protection laws poses significant challenges in terms of storing and analyzing such data. The lack of historical data on workers leads to skewed data, thereby complicating the initial extraction of the model.

**C4: Data Privacy:** The significance of data privacy is paramount today. Therefore, data collection by tracking of workers must be done ethically and follow legal standards to avoid privacy issues. Consequently, the modeling of relevant worker behaviors might need to depend on anonymized or synthetic data, presenting additional complexities in extracting and understanding the underlying structure.

## 4. A Framework for Data-driven DTs for Labor-Intensive Manufacturing Systems

As a result of our literature review and pointing out key challenges, we propose an extension to the framework originally presented by Friederich et al. to create data-driven DTs [7, 20]. This framework focuses on extracting stochastic Petri nets (SPNs) from machine-dominated manufacturing systems. In our extension, we use these extracted models as basic models and enhance them by adding human elements to it, such as fatigue or mood. We exemplify our framework in Section 5 through a case study on improving decision support for job scheduling in a hybrid machine-worker environment by considering well-being of workers. Figure 1 shows our proposed framework for generating DTs for LIMSs using data-driven techniques, where the dark grey part shows the extraction of the machine-dominated models, based on the work of Friederich et al. The framework can be divided into four distinct steps: raw data acquisition, data processing, model extraction, and insight generation.

1. **Raw Data Acquisition:** The first step is to acquire the needed data. As described earlier, it is important to know the goal of the DT and map it to the appropriate data points to establish the required data streams. Apart from the event and state data used by Friederich et al. in the context of machine-dominated systems [7], the inclusion of worker data and environmental data becomes essential for LIMSs. It is important to note that sensors for collecting these additional data points should be as non-intrusive as possible, and their introduction should be communicated in a manner that fosters intrinsic motivation and support from the workers. This would also positively impact the adjustment period and lower the additional stress put on workers.
2. **Processing Data:** Subsequently, data is processed and prepared. This data processing phase is critical to ensure that the data is valid and suitable for analysis. We divide this phase into three tasks:
   *Data Preprocessing:* In this stage, the data is cleaned and transformed to ensure its quality and usability. Common tasks include handling missing data, removing outliers, and addressing any data inconsistencies.
   *Event Log Generation:* Event logs are essential for extracting the basic DT models. The minimal required entries in an event log are timestamps and event types.
   *Worker Log Generation:* Worker logs capture data related to the actions and behavior of workers. The specific data points included in worker logs can vary based on the goals of the DTs and the nature of the task or processes in place. The minimal required entries for worker logs depend on the objectives of the DT and can include data such as task assignments, task starting/completion times, and worker-specific performance metrics.

3. **Model Extraction:** Model extraction is one of the core functionalities for all DTs. In the case of DTs for LIMSs, at first, a basic model is created using process mining techniques on event logs. This basic model describes aspects such as the sequence of tasks in the workflow, estimates of the duration of each step, possible waiting times, and task dependencies. One way of representing the basic model is with SPNs [21]. We chose SPNs for their ability to model discrete-event systems, represent complex manufacturing systems and processes, capture randomness and concurrency, while remaining relatively easily interpretable for non-experts. The basic model is subsequently enhanced by adding worker-related features, facilitating the incorporation of human-related elements of LIMSs. These features can be derived from existing data points or directly measured. This model enhancement ensures that DTs reflect not only machine-related processes but also the intricate dynamics of the workforce, enabling more comprehensive models of manufacturing systems. Afterwards, the extracted models have to be validated to ensure their accuracy. Friederich and Lazarova-Molnar propose an approach to automate validation of data-driven models in a DT setup [22]. Incorporation of domain experts with deep real-world knowledge of the systems provides additional qualitative dimension to the validation process, enabling a thorough examination of a model's alignment with the actual operational practices, as well as the detection of novel insights that may not be obvious from data alone.
4. **Insight Generation:** Lastly, DTs benefit from their simulation capabilities, for instance, by evaluating "what-if" scenarios. By altering variables, adjusting parameters, or introducing hypothetical changes, through simulation, it is possible to assess the potential impact on a given manufacturing system. For example, decision-makers can investigate how changes in task sequences or resource allocations may affect efficiency, or how adjustments to worker assignments can optimize the use of human resources. Equally, on an operational level, a DT can support the manufacturing process by monitoring critical KPIs, sensor values, etc., and suggesting appropriate actions once predefined thresholds are surpassed.

## 5. Illustrative Case Study

To illustrate our proposed framework in a practical context, we developed a case study based on our project collaboration with two companies that feature LIMSs: one in the food production industry, and the other is a pharmaceutical supplier. Both companies share the goal of improving the decision support for job scheduling within a hybrid machine-worker environment by considering workers' well-being. In the following, we describe the process of building the case study, referring to the main aspects of our proposed framework, as well as the encountered challenges, described and summarized in Table 2. In this table, we give a brief description of how we encountered the challenges and their associated risk. The risk is quantified on a discrete scale ranging from 0 to 5, with 5 representing the highest risk. We derived the value considering factors such as the time invested to identify a tailored solution within the case study, the potential disruption to accomplishing overarching objectives, and anticipated financial implications.

| **Challenge** | **Description** | **Anticipated Risk Level** |
|---|---|---|
| Dynamic Manufacturing Systems | Both companies have highly flexible manufacturing processes, driven by the adaptability of the workers. It is imperative to model this adaptability alongside the dynamic changes in manufacturing processes. While the data-driven approach proves effective in managing changes for the basic model, the present iteration assumes a relatively static worker context with the intention of refining it as our research progresses. | 4 |
| Capturing Human Operations | Capturing workers' operations has the biggest impact on the model extraction as there are no wearables or similar in place to generate data regarding the worker processes. Consequently, models are built using derived secondary data, as described in Section 5. | 5 |
| Data Availability | Data availability is very low since both companies are in the early stages of their digital transformation. This applies to both machine- and worker-related data. | 5 |
| Data Privacy | While exploring options for sensors or solutions to improve the data availability of worker operations, we were consistently confronted with challenges related to data privacy. These concerns pose considerable barriers and will significantly affect the implementation process. | 4 |

Table 2. Summary of challenges encountered and their anticipated risk level (0 = low risk, 5 = high risk).

**Raw Data Acquisition:** To simulate the LIMSs of both companies, we created two discrete-event simulation models as streaming data was not yet available. We used these models to inform companies about the sensors that will be required for enabling DTs. In these simulations, we incorporated a fatigue function for each worker, reflecting their productivity over time, and considered their inherent characteristics, including skill level, productivity, and recovery rate. Our models also accounted for machine reliability, factoring in potential breakdowns and subsequent repairs or replacements. We refer to these models as ground-truth models. The validity of these models was verified in collaboration with domain experts from both companies.

**Processing Data:** Once we developed these ground-truth models, we identified the necessary data sources to generate data to enable ground-truth model discovery/extraction. The objective was to facilitate generation of event logs containing time-stamped event records (e.g., ”machine busy/idle”) and condition records (e.g., ”machine failure/repaired”). In our case study, we simulated continuous fatigue levels for each worker based on previous research by [12] and [23], with the aim of discovering what data needs to be collected from the real systems for this purpose.

**Model Extraction:** Utilizing process mining tools, we extracted the basic models as SPNs for both cases, initially without capturing human characteristics [24]. Next, we focused on developing more human-centric models. For this, we used timestamps of the start and end events of the workers' tasks from the event log to estimate tasks' durations. We used these task durations to extract a fatigue model. The extracted fatigue model was translated into an extension of the SPN, wherein the transition distributions were fitted by the fatigue model. As a result, the SPN incorporates the machine-related processes with the associated reliability issues, and the workers with their fatigue over time. Thus, creating a more accurate model of the LIMSs. In Figure 2, we illustrate a simplified sample model inspired by the two use cases, given that the detailed specifications of the actual models are bound by a nondisclosure agreement. This model integrates machine and human components, each characterized by specific reliability and fatigue properties.

**Insight Generation:** In close cooperation with decision-makers of the companies, we used these models to develop a set of ”what-if” scenarios that could support decisions regarding job scheduling in their specific contexts.

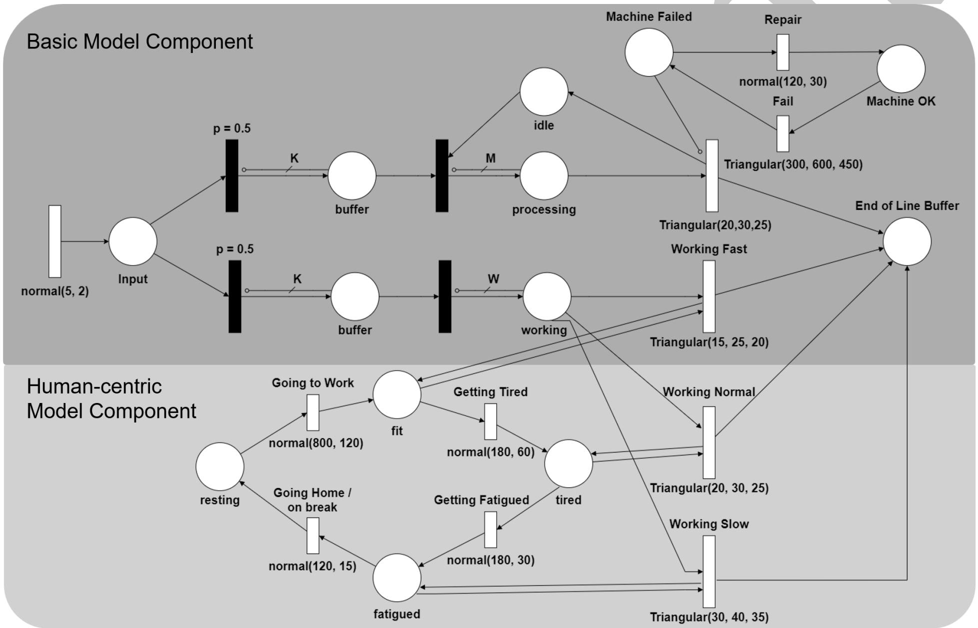


Fig. 2. Simplified sample model based on the two use cases.

## 6. Conclusion

In this paper, we presented the significant challenges with creating DTs of LIMSs, including the complexities of dynamic manufacturing systems, the task of capturing human operations, issues related to data availability, and the ever-present concern of data privacy. We, furthermore, introduced a framework for data-driven DTs of LIMSs that serves as an initial step towards overcoming these challenges. Finally, we applied the framework in a real-world context through a case study, highlighting the challenges and their risk for the project. In addition, the models of the case studies' production lines' helped to determine what data and sensors are required to enable the automated model extraction for DTs. Our ongoing research focuses on addressing the challenges outlined in Section 3 and on refining the proposed framework. We specifically aim to enhance the human-focused model component, ensuring a more accurate representation of the nuances inherent in human work.

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