Production & Manufacturing Research
An Open Access Journal

ISSN: 2169-3277 (Online) Journal homepage: www.tandfonline.com/journals/tpmr20

Human professional skills assessment based on a modified learning curve model

Angela Lago Alvarez, Wael M. Mohammed & Jose Luis Martinez Lastra

To cite this article: Angela Lago Alvarez, Wael M. Mohammed & Jose Luis Martinez Lastra (2025) Human professional skills assessment based on a modified learning curve model, Production & Manufacturing Research, 13:1, 2525935, DOI: 10.1080/21693277.2025.2525935

To link to this article: https://doi.org/10.1080/21693277.2025.2525935

Published online: 03 Jul 2025.

PRODUCTION & MANUFACTURING RESEARCH
2025, VOL. 13, NO. 1, 2525935
https://doi.org/10.1080/21693277.2025.2525935

Human professional skills assessment based on a modified learning curve model

Angela Lago Alvarez, Wael M. Mohammed and Jose Luis Martinez Lastra

FAST-Lab, Faculty of Engineering and Natural Sciences, Tampere University, Tampere, Finland

ABSTRACT
The rapid development of automation and digital technologies poses significant challenges and opportunities for the future of work. One of the key issues is keeping the Human-in-the-loop while enhancing workers´ professional skills to adapt to the dynamic demands of the labour market. Within this gap, this paper proposes a novel approach that integrates a modified version of Wright´s Learning Curve model and an upskilling model. The aim is to capture the skill learning progress by performing repetitive tasks and categorizing them into different skill levels. Finally, to demonstrate the approach, a case study of a manually executed workstation of a manufacturing process is introduced.

ARTICLE HISTORY
Received 14 March 2024
Accepted 19 June 2025

KEYWORDS
Human-in-the-loop; Industry 5.0; professional skills; learning curves

1. Introduction

In the manufacturing domain, Human-in-the-loop and human-centric design are terms that reflect the importance of developing methods and systems that capitalise on the human presence rather than replacing it (Mosqueira-Rey et al., 2023). This has been notability observed in recent years when the concept of Industry 5.0 has been revealed. Such importance is driven by the need for human skills in industries where automation might struggle to fill the gap (Grosse et al., 2023). As an example, the dexterity that humans provide in the manipulation of materials and products, or the cognitive and perception capabilities of humans are well-advanced relative to the capability of machines, AI and robots. Hence, human professional skills must be developed and maintained at an acceptable level.

In the literature, human skill is defined as the ability to perform a task well within a specific process. The human skill set is categorised as soft skills and hard skills (Gallardo, 2020). Soft skills activities are related to living in a community and interacting with other individuals and groups. This might include coordination and leadership, interpersonal and communication skills among others. The hard skills, on the other hand, are related to accomplishing tasks at work. These skills, also known as professional skills, are acquired and can be improved through various methods, primarily through learning and practice. In addition, these skills are needed by

CONTACT Angela Lago Alvarez angela.lagoalvarez@tuni.fi FAST-Lab, Faculty of Engineering and Natural Sciences, Tampere University, Tampere 33720, Finland

employers to examine the human's ability to do certain jobs. Besides that, soft skills are also required at work as most of the jobs include human interactions and communications. Therefore, the required working skills can be a combination of both the soft skills and the hard skills.

With the recent drive to adopt sustainable and human-centric approaches, many manufacturing industries face challenges in terms of human workers' adaptability to match the required skills (L. Li, 2022). This challenge results from the rapid change in the processes and tasks, affecting the worker's required skills. To address this, human skills management ensures the skill development of the workers reaches an acceptable level (Morandini et al., 2023). This development includes reskilling and upskilling the human worker. According to (CARSA and European Innovation Council and SMEs Executive Agency, 2024) reskilling refers to training human workers on a new skill to perform a different job or transition to a different career path. The upskilling term refers to adding a new skill to the worker's skill set or enhancing existing ones to improve an individual's capabilities, often within their current job or field. The main challenge in a worker's skill management is the assessment phase of the skills where the worker's skill level is defined (Mourtzis et al., 2023; Sonal et al., 2024). Not considering the skill level or wrongly assessing the operator's skill level when allocating them may cause ineffective allocation, which can reduce the production efficiency.

With that, the EU Commission has funded a project known as AI-Powered Human-Centred Robot Interactions for Smart Manufacturing (AI-PRISM) (European Commission, 2022). AI-PRISM aims to provide tools to improve Human-Robot Interaction in smart factories. Within the project, a critical need has raised in terms of modelling human workers' skills and assessing skill improvement. In this regard, this article aims to present a systematic method to evaluate human worker skills. This assessment considers the learning aspect of the task concerning the number of products produced by the worker.

The remainder of this paper is structured as follows: Section 2 presents a literature review on related state-of-the-art topics concerning human professional skills in manufacturing, human resource allocation and skill learning models. Then, section 3 presents the approach which includes the modified learning model, and the formulation of the skill-level upgrading model Section 4 describes the implementation of the developed approach using a real data set. Finally, section 5 concludes the article and presents the possible future work.

2. State-of-the-art

2.1. Human skills in manufacturing

The rapid evolution of manufacturing production systems in recent years has led to a transformative era, from Industry 4.0 to the paradigm of Industry 5.0 (Leng et al., 2022; Xu et al., 2021). Industry 4.0 marked a significant milestone in the manufacturing sector, characterised by the integration of digital technologies, automation, and data-driven processes (Durão et al., 2018). However, as we advance towards Industry 5.0, the landscape is shifting to a more human-centric approach, placing human operators at the centre of the production ecosystem (Cortés-Leal et al., 2022; Leng et al., 2022; Longo et al., 2020).

Industry 5.0 (Industry 5.0 2022) represents an answer to the limitations encountered in Industry 4.0, such as the dehumanisation of the workplace and the dependence on automation. This new paradigm seeks to harmonise the benefits of automation and digitalisation with the strengths of human operators such as their adaptability and creativity, as reflected by (Grosse et al., 2023). They acknowledge that humans are not just passive observers in the manufacturing process, but they can act as active collaborators, problem-solvers, and decision-makers (Sgarbossa et al., 2020). In this sense, it is necessary to empower and upskill human operators to work alongside different new technologies, creating a more flexible and adaptive production environment. Understanding and enhancing human operators skills are essential for optimizing the performance of manufacturing production systems (Herder et al., 2014; X. Li et al., 2023). To achieve this, it becomes essential to model and analyse the performance of human operators.

When referring to human skills, the concept has been used broadly and with different interpretations based on the field. For example, the European Commission Skills, Competences, Qualifications and Occupations project (ESCO) and the European Qualifications Framework (EQF) have different visions of what a skill is. ESCO describes the ESCO skills pillar, which distinguishes between i) skill/competence concepts and ii) knowledge concepts by indicating the skill type, with no differentiation between skill and competence (Hart et al., 2021). The EQF states that skill is 'the ability to apply knowledge and use know-how to complete tasks and solve problems. Skills are described as cognitive or practical.' and they separate skill from competence (European Centre for the Development of Vocational Training, 2014). To harmonise the definition of this concept, the European Commission recently published a document unifying a conceptual framework of skills and competences (Rodrigues et al., 2021). Human skill is defined as the ability to perform a task well. Although a skill is an attribute of individuals, it inherently refers to a specific activity (meaning a discrete task within a particular process). Consequently, each task has an associated skill, and its completion depends on the proficiency of that skill. Skill is a relative concept, as one can vary in proficiency from very skilled to not very skilled in performing a particular task, with this gradation being unique to each type of task. For example, authors in (Tervo et al., 2010) applied this definition in the evaluation of the operators´ skills in partially automated mobile working machines to provide feedback.

In the manufacturing context, the operator's role is complex, encompassing many responsibilities such as operating machinery and ensuring the quality of products and processes. Thus, it is essential to examine the skills required for operators to thrive in human-centric manufacturing systems. Previous research (Azizi et al., 2010; Duan et al., 2010; Ericsson et al., 2018) has analysed the skills of workers and modelled them utilizing different approaches and frameworks. These models aim to capture and assess the skills, competencies, and performance of the workforce including diverse factors that act as constraints (Duan et al., 2013; Gräßler et al., 2021). Common ways to model the skill set of the workers include competency or skill-based matrix models, where a set of skills are defined and are expected from workers to evaluate their performance based on their ability to demonstrate them. Evidence of the applicability of this model is presented by the authors in (Houé et al., 2011; Khalil et al., 2019). Another type of modelling includes human performance models, that simulate and predict worker performance based on their skills. These models can be used to assess the impact of different factors on worker performance, such as the introduction of new technologies. Examples of such models include the Cognitive Work Analysis Model (Higgins, 1998; Rasmussen & Pejtersen, 1990) and the Human Error Modelling (Leiden et al., 2001). Machine learning and data-driven models are also increasingly being used to model worker skills. These models analyse data related to worker performance and job requirements to identify skill gaps and make recommendations for skill development. Additionally, there are some other popular models, such as skill taxonomies that categorize and organize skills into a hierarchical structure (Hammerstingl & Reinhart, 2018). Moreover, by drawing upon insights from existing research, this chapter aims to shed light on the central role played by human operators in this landscape and how their skills can be exploited to foster innovation and efficiency.

2.2. Human resources allocation in industrial environments

Optimising human resources allocation in factories is a critical aspect of industrial management. It involves assigning the right employees to the proper tasks, considering different factors such as availability, skill level, and experience (Beauchemin et al., 2023; Said et al., 2016). Depending on the target of the optimisation, it can enhance efficiency by ensuring that each task is performed by the most qualified individual. Additionally, when employees are assigned tasks that are aligned with their skills and interests, their satisfaction and engagement levels are elevated. In return, improves the workforce's morale. In case the target of the optimisation is increasing the quality control, assigning qualified individuals to the tasks tends to reduce the errors. Overall, the ability to reallocate resources quickly and efficiently in a dynamic industrial environment provides the flexibility for companies to adapt to changes and maintain operations. As an example of the previous statements, authors in (Zhao et al., 2020) discuss how impartial allocation of human resources can maximise resource efficiency and optimise business performance by analysing team failures in human resources allocation.

Optimising the allocation of human workers in factories is a well-documented problem exploited broadly in the literature (Arias et al., 2018; Bouajaja & Dridi, 2017). In the context of this paper, the optimisation of human resource allocation will be approached with a focus on the skills of the workers, a strategy that aligns with the human-centric approach of the Industry 5.0 paradigm. In the domain of human resource allocation, there exist some commercial solutions that incorporate employee skills into their resource distribution strategies. Table 1 presents a comparison of these commercially available solutions.

As shown in Table 1, these commercial solutions can help optimise the allocation of human resources varying the method they incorporate the worker´s skills. Smartsheet and Resource Guru provide approaches that allow for resource allocation optimisation based on skill sets, yet lacking in skill introduction or calculation, and in automating resource allocation or providing allocation recommendations based on targets. While Saviom and Mavenlink offer an advanced method of skill management, they do not fully

Table 1. Comparative of commercial human resources allocation solutions.

Software	Description	Advantages	Disadvantages	Consideration of Employee's Skills
10,000ft by Smartsheet (Benelisha, 2019)	A project management tool that provides high-level resource allocation and project planning.	Customizable and powerful, robust resource management and team collaboration tools.	Lacks real-time time tracking and updating. Pages, data and assignments do not update in real-time, which can impact collaboration and decision-making.	It allows for the optimisation of resource allocation by constraint or skill set. It does not specify the enhancement mechanism or the way to introduce or calculate the skill set.
Resource Guru (Guru, 2023)	A resource management software that offers a simple way to schedule people, equipment, and other resources online.	Fast and intuitive scheduling, capacity planning, and time tracking.	Limited integrations with other tools. Manual allocation of resources.	It allows for the organization of resources based on skills and other criteria but does not allocate the assets automatically or provide allocation recommendations based on targets.
Saviom (Resource Management & Professional Service Automation, 2023)	An enterprise-level resource management tool that includes features for skills tracking and resource allocation based on skills.	Detailed analytics, intuitive resource scheduling, and adaptive workflows.	Long onboarding process, integration limitations, customisation dependency.	It allows for the creation of a library of custom skills that can be assigned to individual team members. It permits the tracking of the skills, but no allocation based on the skill constraint.
Mavenlink (Mavenlink Professional Services Automation & Resource Management, 2023)	A project planning tool with features that help create detailed project plans and productivity tracking.	Detailed project plans, productivity tracking, and stringent accounting.	Not specified.	Yes, it allows for the creation of a library of custom skills that can be assigned to individual team members. It permits the tracking of the skills, but no allocation based on the skill constraint.

address resource allocation based on skill constraints. These tools lag behind research in providing comprehensive skill-constrained resource allocation. Organisations may need to consider a combination of different tools, custom solutions to achieve optimal resource allocation or combine existing tools with research insights.

This section revealed the importance of optimising human resource allocation, focusing on the workers´ skills as a key factor. To achieve this, some commercial solutions were explored but do not offer a fully automated and intelligent approach to allocate resources based on the skill set approach.

2.3. Learning models in the literature

The evolvement of the manufacturing industry from Industry 4.0 to 5.0 underscores the importance of human operators in the production process. This section highlights the need to understand how human operator skills are acquired and retained. To explore these dynamics, the Learning Curve Theory could contribute to exploring the development and maintenance of human operator skills with the development of learning curve-based models.

In broad terms, learning curve models are based on the premise of the learning curve (LC). LC is a fundamental concept that shows how the time required to produce a unit decreases as the cumulative production increases. Moreover, in the manufacturing sector, these *workforce learning curves* refer to 'the mathematical description of the performance of a worker through time' (Wright, 1936). There are different types of LC model based on their mathematical representations and considerations. Table 2 illustrates some of the most well-known models classified by their mathematical representation.

Where y is the average time or cost per unit and x defines the number of units produced in all previous learning models. In Log-linear models, C_1 is the time or cost for the first unit and b represents the learning coefficient parameter. The constant term C represents the standard time estimated from empirical data in the Plateau model. In Stanford-B, DeJong´s, and S-curve models, parameter B accounts for the worker's prior experience in the number of units of experience, and parameter M is the fraction of the task executed by machines. Regarding Exponential and Hyperbolic models in the table, k represents the maximum throughput of a worker after the learning curve slope approaches zero, parameter r represents the learning rate in time units and p corresponds to the worker's prior experience, expressed in time units.

Log-linear models suggest that the time or effort required to complete a task decreases with experience or repetition (Badiru, 1992; M. Jaber, 2006). These models assume a consistent learning rate with steady, gradual improvements, suitable for repetitive tasks with long-term focus. In manufacturing, these models imply that as operators gain experience, they become increasingly efficient. Modifications may include factors such as the introduction of new equipment or training. Another type of models are the exponential ones, which assume that learning and skill improvement follow an exponential curve. In contrast to log-linear ones, exponential models emphasise rapid initial improvements that taper off, leading to a performance plateau. These are ideal for scenarios requiring quick mastery followed by stable performance such as describing the early stages of operator skill development (Peña et al., 2022). The last type of LC models are hyperbolic models. These models have become relevant due to their capacity to show both the increase and decrease of cycle time. The learning curve model choice depends on the specific context and characteristics of the manufacturing process (Peña

Table 2. Comparative of learning models.

Learning Curve Model	Type	Mathematical Representation
Wright model (Durkin, 2019; Smunt, 2000)	Log – linear	$y = C_1x^b$ (1)
Plateau model (Mirzaei & Zoghi, n.d.)	Log – linear	$y = C + (C_1 - C)x^b$ (2)
Stanford – B model (Grosse & Glock, 2013)	Log – linear	$y = C_1(x + B)^b$ (3)
DeJong´s model (Grosse & Glock, 2013)	Log – linear	$y = C_1\left[M + (1 - M)x^b\right]$ (4)
S-curve model (Dam, 2018)	Log – linear	$y = C_1\left[M + (1 - M)\left(x + B\right)^b\right]$ (5)
2 - Parameter exponential model (Anzanello & Fogliatto, 2011)	Exponential	$y = k\left(1 - e^{-\frac{x}{r}}\right)$ (6)
3 - Parameter exponential model (Anzanello & Fogliatto, 2011)	Exponential	$y = k\left(1 - e^{-\frac{(x+p)}{r}}\right)$ (7)
2 - Parameter hyperbolic model (Dar-El, 2013)	Hyperbolic	$y = k\frac{x}{(x+r)}$ (8)
3 - Parameter hyperbolic model (Grosse & Glock, 2013)	Hyperbolic	$y = k\frac{x+p}{(x+r+p)}$ (9)

et al., 2022). Log-linear models are often suitable for tasks that require consistent repetition and improvement, while exponential and hyperbolic models are well-suited for capturing the nuances of early and later learning stages, respectively (Dar-El, 2013; Schilling et al., 2003).

Overall, the industry´s transition emphasises the role of human operators in the production process, raising the need for a deeper understanding of operator skills. Learning models provide valuable insights into how they are acquired and retained. These models offer mathematical representations of how the performance of a worker evolves. Each model type captures different aspects of the learning process, making them suitable for different contexts and stages of skill development. The choice of learning model should be thoughtfully evaluated, considering the specific context and characteristics of the manufacturing process. Future research and development efforts should focus on creating more sophisticated models and tools that can incorporate them into resource allocation strategies.

3. Approach

In the previous section, the importance of mapping and improving workforce technical skills was highlighted. The authors (Alvarez et al., 2023) present an innovative approach for incorporating human factors into digital twins. They introduce a methodology that offers suggestions about employee rotations based on their previous performance during a shift considering their skills. The skills are organised and updated following a multi-attribute skill matrix reviewed by an expert every six or twelve months. Then, this method is integrated into a Digital Twin (DT) to perform human performance assessments to manage workers' jobs. This paper aims to extend and enhance the workers' skills assessment process by introducing an approach to automate workforce skills upgrades based on their skills learning processes.

Before delving into the specifics of the approach, it is important to establish the terminology and assumptions used throughout this paper. In the context of a manufacturing process, operators perform various activities referred to as 'production tasks', to complete a product. The execution of these tasks is repetitive over time and influenced by various environmental conditions, such as ergonomic factors. Production tasks are ruled by quality requirements and time constraints. They are defined as a series of operations, each corresponding to a specific skill following the unified definition. This forms the basis of the analysis in the following subsections of this paper. These terms and assumptions are crucial for understanding the concepts presented in this paper.

3.1. Modified learning curve model formulation

As was emphasised in the literature, learning curve models provide a mathematical description of the performance of a worker through time. LC models, which were formulated several years ago, may now be considered antiquated due to the advancements and evolution in the manufacturing processes. Considering these models, the challenge at the core of this research lies in designing a unified learning model that can represent the work of operators and their skills. This model should exhibit the versatility required to be applicable across various manufacturing processes, and represent how well the skills are performed rather than the cost or time consumed in production. Besides presenting the learning progress of the worker, as is often found in the existing literature (Globerson, 1987; Hoedt et al., 2020; M. Y.; M. Y. Jaber & Sikström, 2004; Nembhard & Uzumeri, 2000), this model also should provide skill level assessment functionality. This approach aims to address the intricacies of human operator skills in manufacturing, offering a more comprehensive understanding and adaptable framework for modelling skill acquisition.

Regarding the learning models, Wright´s LC model was chosen to be the foundation of this approach since it focuses on the idea that as workers repeat a specific task, they become more skilled and efficient. This assumption works within the scope of this research, and it presents several advantages, such as this model can help in predicting future performance based on past learning experiences and it was tested in industrial environments. However, Wright's LC model presents some limitations. For instance, the relationship between the amount of time invested in performing an activity and overall performance is not strictly linear. There will be periods where a small amount of work results in substantial improvement in output, and conversely, periods where significant effort leads to minimal gains. Additionally, this model considers the premise of time or cost to perform a product as quantitative metrics.

Considering the aforementioned arguments, the authors propose the following modifications for Wright´s LC model in Equation 10:

$$y = (|Xsup, A - NMV|)x^b \tag{10}$$

where $Xsup, A$ corresponds to the maximum measured value of a metric in which a worker can perform a product (Alvarez et al., 2023), y represents how far performance is from the ideal one, x and b maintain the same meaning as in the original model, and NMV is the abbreviature of Nominal Measured Value which defines the theoretical measure of the metric in which the tasks should be carried out.

Rather than compiling the average time or cost associated with the production of a product, to minimize these values, the authors suggest a novel approach: quantifying the deviation of the performance from the NMV. In the graphical representation of the model presented in Figure 1, the baseline on the x-axis corresponds to a value of 0 and indicates the ideal performance. The greater the deviation from 0, the larger the room for enhancement. This allows for a quantifiable measure of skill or performance progression. A benefit of this method is the generation of a normalised model, which is advantageous for comparing skill or performance in future research. Moreover, this approach is not limited to time-based measurements; it is versatile enough to incorporate any measurement that signifies skill enhancement.

3.2. Skill-level upgrading model formulation

The concept of the learning curve is refined through the integration of a skill-based approach. Considering the representation provided in Figure 1, the area beneath the curve represents the skill-learning cost a worker is likely to encounter in achieving optimal performance for a specific task. The proposed method aims to bind the skill levels of the workers to their learning processes by defining zones

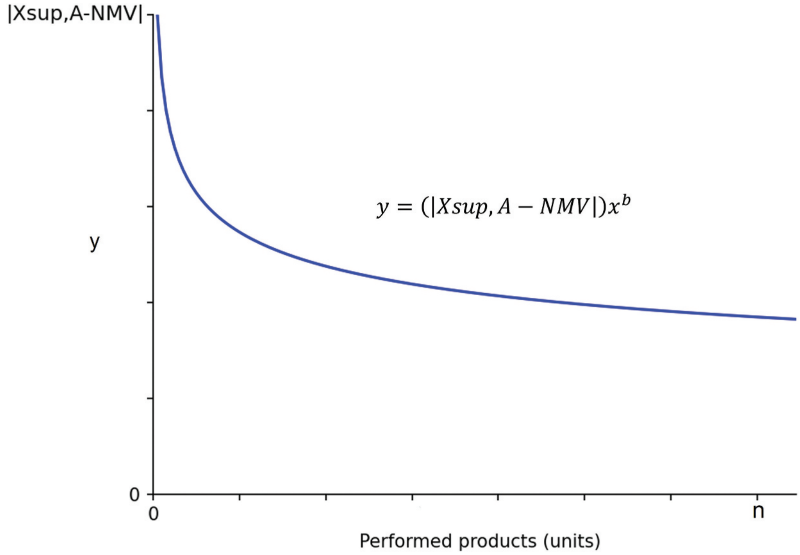

Figure 1. Generic graphical representation of the modified LC model.

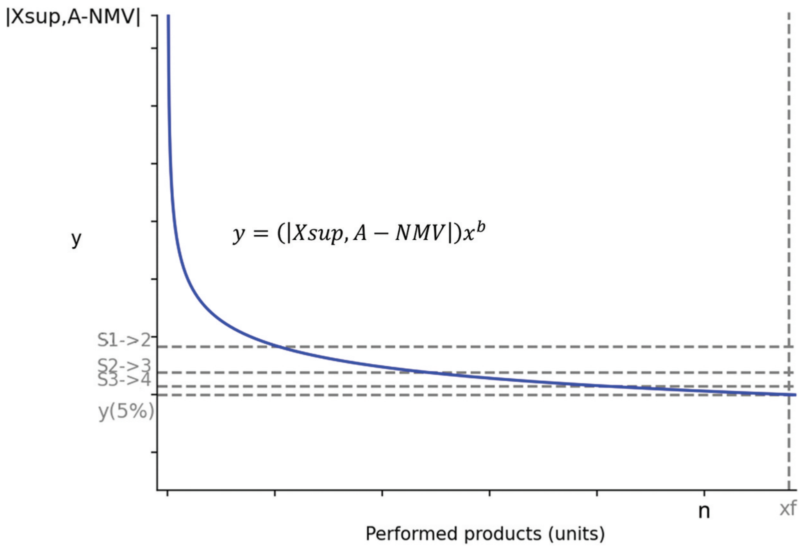

Figure 2. Generic modified LC model with skill-level references.

of skill acquisition within the LC model, as depicted in Figure 2. In this Figure, the skill levels are categorised from 1 to 4 following the skill level framework (Alvarez et al., 2023). These segments correspond to the worker's skill levels achievable during the repetitive execution of the task. This enhancement can facilitate the allocation of workers as the assignment is based on the skill level, a key aspect in the conceptual framework of this research. Furthermore, the automation of skill upgrades, derived from the LC model, provides valuable recommendations for adjusting the workforce's skill levels. This innovation enhances prior work by eliminating the need for manual selections or expert reviews within the multi-attribute skill matrix.

To carry out the computations, the initial step involves calculating the total area under the curve (denoted as A) utilising the procedure presented in Equation 11:

$$A = \int_1^{inf} (|Xsup, A - NMV|) x^b dx \tag{11}$$

The area under the curve represents an improper integral due to the presence of an infinite limit of integration. Additionally, the function presents asymptotic behaviour at × = 0 and y = 0. To solve it, the integral is set up from × = 1 to a finite number d. Then, this integral is evaluated conventionally, giving an approximation of the area under the curve from × = 1 to ×= d. Subsequently, to extend the upper limit to infinity, the limit as d approaches infinity is computed in Equation 12:

$$A = \lim_{d\to\infty} (\int_1^d (|Xsup, A - NMV|) x^b dx) = \lim_{d\to\infty} (\left[\frac{(|Xsup, A - NMV|) x^{(1+b)}}{(1+b)} \right]_1^d) \tag{12}$$

As d approaches the infinity, this limit represents the precise value of the area under the curve from (x = 1) to infinity. Mathematically, the limit diverges, as its solution extends to infinity. In the context of this research, the mathematical challenge is addressed by calculating d as 5% of the initial value at x = 1. By adopting this approach, the ideal performance level is approximated since a worker who performs within this 5% range is already an expert (skill level 4) in the learned task. For clarity, Figure 2 visually illustrates this assumption. The 5% threshold for ideal performance is mathematically expressed in Equation 13 and the corresponding value of (x) at the 5% threshold is given by Equation 14.

$$y(5\%) = 0.05 \times (|Xsup, A - NMV|) \tag{13}$$

$$xf = \sqrt[b]{0.05} \tag{14}$$

By incorporating these assumptions (Equations 13 and 14) into the existing framework (Equation 12), the resultant area (A) under the curve is obtained in Equation 15:

$$A = \frac{|Xsup, A - NMV|}{1+b} \times \left(0.05^{\frac{1+b}{b}} - 1\right) \tag{15}$$

Once the total area is calculated, the zones of skill levels can be computed. In this regard, the convention in this research includes dividing the area, which is calculated by Equation 15, into four equal zones (each zone represents a skill level). In this matter, each transition between the zones (skill levels) requires the same effort. This way, Equation 16 represent the necessary production volume for a worker to achieve the upgrade from skill level 1 to skill level 2.

$$x_{1\to2} = \sqrt[(1+b)]{\frac{0.05^{\left(\frac{1+b}{b}\right)} + 3}{4}} \tag{16}$$

Equations (17) and 18 represent the equivalent for the upgrade from skill level 2 to skill level 3 and 3 – 4.

$$x_{2\to 3} = \sqrt[(1+b)]{\frac{0.05^{\left(\frac{1+b}{b}\right)} + 1}{2}} \tag{17}$$

$$x_{3\to 4} = \sqrt[(1+b)]{\frac{3 \times \left(0.05^{\left(\frac{1+b}{b}\right)} - 1\right)}{4} + 1} \tag{18}$$

Additionally, Equations (19), 20, and (21) estimate the corresponding time required for each skill level upgrade.

$$h_{1\to 2} = \frac{x_{1\to 2} \times NMV}{3600} \tag{19}$$

$$h_{2\to 3} = \frac{x_{2\to 3} \times NMV}{3600} \tag{20}$$

$$h_{3\to 4} = \frac{x_{3\to 4} \times NMV}{3600} \tag{21}$$

4. Implementation

To implement the proposed approach, data from an assembly line was collected. The dataset contains shopfloor timestamps from a manually executed workstation performed by different operators. The task performed include the assembly of the front door of a washing machine, where the operator takes one door from the door´s cart, place it in the machine and secure it with screws. Then, the worker closes the door and visually inspects that it is correctly assembled. Time recording starts when a product arrives at the workstation and ends when the operator performing the task, presses a button indicating that the task is finished. The collected dataset contains around 45,000 datapoints including a few outliers. After the cleaning process 38,000 datapoints have been kept, which produced an improvement on the realism of the result. The cleaned dataset yielded a mean cycle time of 19.12 seconds with a standard deviation of 6.33 seconds, indicating moderate variability in the observations.

Before defining the modified LC model, it is essential to calculate or estimate the learning coefficient parameter proper for the model. As this is a data-driven approach, the learning coefficient will be calculated based on real data.

4.1. *Learning coefficient parameter calculations*

The learning coefficient is the learning parameter that represents the rate at which improvement takes place. Usually, it is expressed in terms of a learning slope p, and it can be calculated using the formula in Equation 22.

$$b = \frac{\log p}{\log 2} \tag{22}$$

Due to the complexity of the dataset available, the learning coefficient is calculated per task performed in the workstation to provide an overall view of the learning process. To proceed with the calculations, additional variables are needed, such as NMW (16.5 s) and $X_{sup,A}$ (35.0 s). The method selected to calculate the parameter p in a linear regression model is to minimize the residual sum of squares (RSS), which measures the discrepancy between the observed and predicted values of the dependent variable. RSS can be expressed as the formula in Equation 23:

$$RSS = \sum_{i=1}^{n} (y_i - y'_i)^2 \tag{23}$$

where y_i is the observed value, y'_i is the calculated value, and n is the number of observations. To find the optimal value of p, the solver is utilised as the numerical optimization technique, which iteratively adjusts the value of p until it reaches the minimum point of RSS. The resolution method is Generalised Reduced Gradient (GRG) Nonlinear and the value p is constrained to be higher than 0.5 and lower than 1.

Following this procedure, a p-value of 0.8650 is obtained, which means a learning slope of 86.5%. This value is acceptable considering the work performed is categorised as general assembly. According to (Dar-El, 2013), the calculated p-value falls within the reference learning slope values of a general assembly workstation.

4.2. Modified learning curve model calculations

Upon the calculation of the learning coefficient utilising the available dataset, the model is subsequently established by Equation 10. The implemented Modified LC Model is expressed in Equation 24.

$$y = 18.5 \times x^{-0.2092} \tag{24}$$

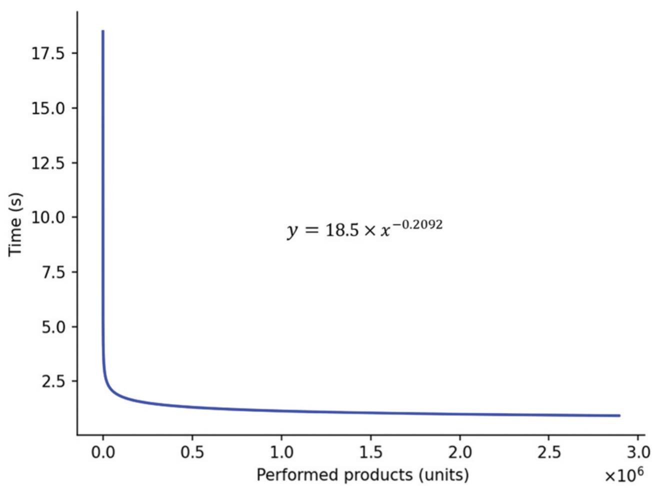

Figure 3. Implementation of the modified LC model.

Figure 3 provides a visual description of this modified LC model. It is crucial to note that this figure is a graphical interpretation of the model as defined by Equation 24. The graph serves to illustrate the relationship between variables, as dictated by the model.

4.3. Skill-level upgrading model calculations

Upon the computation of the LC model, the zones of skill acquisition can be defined. Figure 4 provides a graphical overview of the areas.

In this Figure, skill levels are categorised from 1 to 4. Each level corresponds to a distinct stage of skill acquisition that a worker can achieve during the repetitive execution of a task. The areas are colour-coded to represent different skill levels:

- The yellow area represents Skill Level 1, indicative of a beginner learner's performance. This stage is characterised by rapid improvement, as evidenced by the steep slope of the curve. Individuals are primarily focused on acquiring the basics of the skill, and they may require significant guidance and supervision.
- The green area denotes Skill Level 2, corresponding to an intermediate learner's progress. The slope of the curve is less pronounced at this stage, reflecting the learner's basic understanding of the skill and their ability to perform tasks under moderate supervision.
- The red area presents Skill Level 3, where workers have developed a solid understanding of the skill.
- The purple area discloses Skill Level 4 performance, the pinnacle of expertise. At this level, individuals possess a deep understanding of the skill, and they are capable of mentoring others.

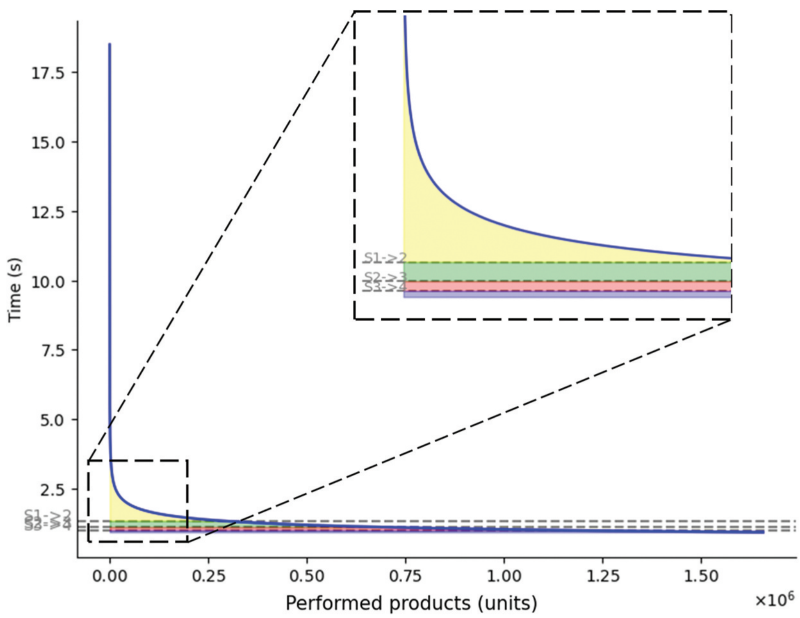

Figure 4. Skill-level upgrading model areas.

Table 3. Skill level zones equations.

Skill level transition	Number of performed products (ud)	Estimated working hours (h)
From skill level 1 to skill level 2	$x_{1\to2} = 287256$	$h_{1\to2} = 1324.57$
From skill level 2 to skill level 3	$x_{2\to3} = 690102$	$h_{2\to3} = 3182.14$
From skill level 3 to skill level 4	$x_{3\to4} = 1152337$	$h_{3\to4} = 5313.55$

For each skill level upgrade, Table 3 outlines the required production volume for a worker to achieve the upgrade, along with an estimation of the time required. These values were derived using the learning model described in Equations (16)–(21).

This enhanced representation of Wright´s LC model, completed with skill-level references and detailed areas, provides a comprehensive framework for understanding and managing the skill acquisition process in a workforce.

5. Conclusions

This paper has explored the key aspects regarding workers´ performance, providing a comprehensive understanding of its intricacies and implications. The proposed approach for updating Wright´s Learning Curve presents several advantages regarding the original method, such as quantifying the deviation of an individual's performance from the ideal, which allows for a quantifiable skill or performance progression. Additionally, the method is a normalised model, which is advantageous for comparing skill or performance in future research and it is not time-based constrained. Furthermore, the model exhibits sensitivity to variations in parameter b. The skill-level upgrading model includes an automated solution for skill level assessment, which help adjust the workforce's skill levels removing the need for expert reviews. While the research has yielded valuable insights, it also opens up avenues for further exploration, such as tailoring the learning coefficient per worker, adding a human factors component to the model and, providing adaptative learning paths or strategic resources allocation using AI. Ultimately, the knowledge gained from this study contributes to the broader academic dialogue and promotes informed discourse on the subject. In addition, is important to verify the proposed approach with sufficient data to corroborate the findings.

Acknowledgments

The research leading to these results has received funding from the European Union's Horizon Europe research and innovation program under grant agreement n° 101058589 which corresponds to the AI-powered human-centred robot interaction for smart manufacturing (AI-PRISM) project.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the European Commission [101058589].

References

Alvarez, L., Angela, W. M. M., Vu, T., Ahmadi, S., & Lastra, J. L. M. (2023). Enhancing digital twins of semi-automatic production lines by digitizing operator skills. *Applied Sciences*, *13*(3), 1637. https://doi.org/10.3390/app13031637

Anzanello, M. J., & Fogliatto, F. S. (2011). Learning curve models and applications: Literature review and research directions. *International Journal of Industrial Ergonomics*, *41*(5), 573–583. https://doi.org/10.1016/j.ergon.2011.05.001

Arias, M., Saavedra, R., Marques, M. R., Munoz-Gama, J., & Sepúlveda, M. (2018). Human resource allocation in business process management and process mining: A systematic mapping study. *Management Decision*, *56*(2), 376–405. https://doi.org/10.1108/MD-05-2017-0476

Azizi, N., Zolfaghari, S., & Liang, M. (2010). Modeling job rotation in manufacturing systems: The study of employee's boredom and skill variations. *International Journal of Production Economics*, *123*(1), 69–85. https://doi.org/10.1016/j.ijpe.2009.07.010

Badiru, A. B. (1992). Computational survey of univariate and multivariate learning curve models. *IEEE Transactions on Engineering Management*, *39*(2), 176–188. https://doi.org/10.1109/17.141275

Beauchemin, M., Ménard, M.-A., Gaudreault, J., Lehoux, N., Agnard, S., & Quimper, C.-G. (2023). Dynamic allocation of human resources: Case study in the metal 4.0 manufacturing industry. *International Journal of Production Research*, *61*(20), 6891–6907. https://doi.org/10.1080/00207543.2022.2139002

Benelisha, D. (2019). *Smartsheet acquires 10, 000ft to enhance resource management capabilities*. Smartsheet.

Bouajaja, S., & Dridi, N. (2017). A survey on human resource allocation problem and its applications. *Operational Research*, *17*(2), 339–369. https://doi.org/10.1007/s12351-016-0247-8

CARSA and European Innovation Council and SMEs Executive Agency. (2024). *Pact for skills: Analysing of up and reskilling policy initiatives and identifying best practices: Final report*. Publications Office of the European Union. https://data.europa.eu/doi/10.2826/324945

Cortés-Leal, A., Cárdenas, C., & Del-Valle-Soto, C. (2022). Maintenance 5.0: Towards a worker-in-the-loop framework for resilient smart manufacturing. *Applied Sciences*, *12*(22), 11330. https://doi.org/10.3390/app122211330

Dam, N. V. (2018). *Elevating learning & development: Insights and practical guidance from the field*. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/elevating-learning-and-development-insights-and-practical-guidance-from-the-field

Dar-El, E. M. (2013). *HUMAN LEARNING: From learning curves to learning organizations*. Springer Science & Business Media.

Duan, F., Gao, Q., & Arai, T. (2010). Assembly skill transfer System for cell production. *2010 IEEE International Conference on Robotics and Biomimetics* (pp. 253–258). https://doi.org/10.1109/ROBIO.2010.5723336

Duan, F., Gao, Q., Zhu, C., Kato, R., & Arai, T. (2013). An assembly-skill-transferring method for cellular manufacturing System—part I: Verification of the proposed method for motor skill. *IEEE Transactions on Automation Science and Engineering*, *10*(2), 465–470. https://doi.org/10.1109/TASE.2013.2240680

Durão, L. F. C. S., Haag, S., Anderl, R., Schützer, K., & Zancul, E. (2018). Digital twin requirements in the context of industry 4.0. In P. Chiabert, A. Bouras, F. Noël, & J. Ríos (Eds.), *Product lifecycle management to support industry 4.0* (pp. 204–214. IFIP Advances in Information and Communication Technology. Springer International Publishing. https://doi.org/10.1007/978-3-030-01614-2_19

Durkin, G. J. (2019). Implementation and evaluation of Wright's competency model. *Journal for Nurses in Professional Development*, *35*(6), 305. https://doi.org/10.1097/NND.0000000000000575
Ericsson, K. A., Hoffman, R. R., & Kozbelt, A. (2018). *The Cambridge handbook of expertise and expert performance*. Cambridge University Press.
European Centre for the Development of Vocational Training, ed. (2014). *Terminology of European education and training policy: A selection of 130 key terms* (2nd ed.). Publ. Office of the European Union.
European Commission. (2022, January 10). *AI powered human-centred robot interactions for smart manufacturing | AI-PRISM project | fact sheet | HORIZON. CORDIS | European commission*. https://cordis.europa.eu/project/id/101058589
Gallardo, A. U. (2020). Significance of high human skills in the success of an organization. *Proceedings of the 17 Th International Symposium on Management (INSYMA 2020)*, Atlantis Press. https://doi.org/10.2991/aebmr.k.200127.099
Globerson, S. (1987). Incorporating forgetting into learning curves. *International Journal of Operations and Production Management*, *7*(4), 80–94. https://doi.org/10.1108/eb054802
Gräßler, I., Roesmann, D., Cappello, C., & Steffen, E. (2021). Skill-based worker assignment in a manual assembly line. *Procedia CIRP*, *100*(January), 433–438. https://doi.org/10.1016/j.procir.2021.05.100
Grosse, E. H., & Glock, C. H. (2013). An experimental investigation of learning effects in order picking systems. *Journal of Manufacturing Technology Management*, *24*(6), 850–872. https://doi.org/10.1108/JMTM-03-2012-0036
Grosse, E. H., Sgarbossa, F., Berlin, C., & Neumann, W. P. (2023). Human-centric production and logistics system design and management: Transitioning from industry 4.0 to industry 5.0. *International Journal of Production Research*, *61*(22), 7749–7759. https://doi.org/10.1080/00207543.2023.2246783
Guru, R. (2023). *Resource scheduling software | project resource scheduling*. Resource Guru. https://resourceguruapp.com/features/resource-scheduling
Hammerstingl, V., & Reinhart, G. (2018). *Skills in assembly*. https://mediatum.ub.tum.de/1428286
Hart, J., Noack, M., & Plaimauer, C. (2021). Towards a structured and consistent terminology on transversal skills and competences. *3rd report to ESCO member states working group on a terminology for transversal skills and competences (TSCs)*. https://esco.ec.europa.eu/system/files/2022-05/MSWG%2014-04%20Report%20of%20the%20expert%20group%20on%20transversal%20skills%20and%20competences.pdf
Herder, C., Baumann, B., & Aurich, J. C. (2014). Assembly-orientated technology mvanagement. *Productivity Management*, *19*(4), 52–54.
Higgins, P. G. (1998). Extending cognitive work analysis to manufacturing scheduling. *Proceedings 1998 Australasian Computer Human Interaction Conference. OzCHI'98 (Cat. No.98EX234)* (pp. 236–243). IEEE Comput. Soc, Adelaide, SA, Australia. https://doi.org/10.1109/OZCHI.1998.732220
Hoedt, S., Claeys, A., Aghezzaf, E.-H., & Cottyn, J. (2020). Real time implementation of learning-forgetting models for cycle time predictions of manual assembly tasks after a break. *Sustainability*, *12*(14), 5543. https://doi.org/10.3390/su12145543
Houe, R., et al. (2011). Fuzzy Logic in Competence Management. Proceedings of the 7th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT-2011), Atlantis Press. https://doi.org/10.2991/eusflat.2011.124
European Commission, (2024). Industry 5.0. [online] 25 July.https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en
Jaber, M. (2006, January). Learning and forgetting models and their applications. *Handbook of Industrial and Systems Engineering*, 30–31. https://doi.org/10.1201/9781420038347.ch30
Jaber, M. Y., & Sikström, S. (2004). A numerical comparison of three potential learning and forgetting models. *International Journal of Production Economics*, *92*(3), 281–294. https://doi.org/10.1016/j.ijpe.2003.10.019

Khalil, H., Byrne, A., & Ristevski, E. (2019). The development and implementation of a clinical skills matrix to plan and monitor palliative care nurses' skills. *Collegian, Palliative Care*, *26*(6), 634–639. https://doi.org/10.1016/j.colegn.2019.05.002

Leiden, K., Laughery, K. R., Keller, J., French, J., Warwick, W., & Wood, S. D. (2001). A review of human performance models for the prediction of human error. Ann Arbor, 1001, 48105.

Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D., & Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, *65*(October), 279–295. https://doi.org/10.1016/j.jmsy.2022.09.017

Li, L. (2022, July). Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond. *Information Systems Frontiers*, *26*(5), 1697–1712. https://doi.org/10.1007/s10796-022-10308-y

Li, X., Nassehi, A., Wang, B., Hu, S. J., & Epureanu, B. I. (2023). Human-centric manufacturing for human-system coevolution in Industry 5.0. *CIRP Annals*, *72*(1), 393–396. https://doi.org/10.1016/j.cirp.2023.04.039

Longo, F., Padovano, A., & Umbrello, S. (2020). Value-oriented and ethical Technology Engineering in Industry 5.0: A human-centric perspective for the design of the factory of the future. *Applied Sciences*, *10*(12), 4182. https://doi.org/10.3390/app10124182

Mavenlink Professional Services Automation & Resource Management. (2023). *Mavenlink professional Services automation & resource management | kantata*. https://www.mavenlink.com/

Mirzaei, M., Zoghi, M., & Davatgari Asl, H. (2017). Understanding the language learning plateau: A grounded-theory study. *Teaching English Language, 11*(2), 195–222. https://doi.org/10.22132/tel.2017.53188

Morandini, S., Fraboni, F., Angelis, M. D., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The impact of artificial Intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science: The International Journal of an Emerging Transdiscipline*, *26*, 039–068. https://doi.org/10.28945/5078

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: A state of the art. *Artificial Intelligence Review*, *56*(4), 3005–3054. https://doi.org/10.1007/s10462-022-10246-w

Mourtzis, D., Angelopoulos, J., & Panopoulos, N. (2023). Manufacturing personnel task allocation taking into consideration skills and remote guidance based on augmented reality and intelligent decision making. *International Journal of Computer Integrated Manufacturing*, *36*(1), 70–85. https://doi.org/10.1080/0951192X.2022.2078513

Nembhard, D. A., & Uzumeri, M. (2000). Experiential learning and forgetting for manual and cognitive tasks. *International Journal of Industrial Ergonomics*, *25*(4), 315–326. https://doi.org/10.1016/S0169-8141(99)00021-9

Peña, C., Romero, D., & Noguez, J. (2022). Workforce learning curves for human-based assembly operations: A state-of-the-art review. *Applied Sciences*, *12*(19), 9608. https://doi.org/10.3390/app12199608

Rasmussen, J., Pejtersen, A. M. & K. Schmidt. (1990). *Taxonomy for cognitive work analysis*. Roskilde, Denmark: Risø National Laboratory. 153 pp. (Risø-M; No. 2871).

Resource Management & Professional Service Automation. (2023). *Resource management & professional Service automation | Saviom*. https://www.saviom.com/

Rodrigues, M., Fernández-Macías, E., & Sostero, M. (2021). *A unified conceptual framework of tasks, skills and competences*.

Said, T., Otman, A., Jaafar, A., & Najat, R. (2016). An optimizing approach for multi constraints reassignment problem of human resources. *International Journal of Electrical and Computer Engineering (IJECE)*, *6*(4), 1907. https://doi.org/10.11591/ijece.v6i4.pp1907-1919

Schilling, M. A., Vidal, P., Ployhart, R. E., & Marangoni, A. (2003). Learning by doing something else: Variation, relatedness, and the learning curve. *Management Science*, *49*(1), 39–56. https://doi.org/10.1287/mnsc.49.1.39.12750

Sgarbossa, F., Grosse, E. H., Neumann, W. P., Battini, D., & Glock, C. H. (2020). Human factors in production and logistics systems of the future. *Annual Reviews in Control*, *49*(January), 295–305. https://doi.org/10.1016/j.arcontrol.2020.04.007

Smunt, T. L. (2000). Learning curve, analysis ofLEARNING CURVE ANALYSIS. In P. M. Swamidass (Ed.), *Encyclopedia of production and manufacturing management* (pp. 353–360). Springer US. https://doi.org/10.1007/1-4020-0612-8_504

Sonal, G., Israrul, H., & Ganesh, S. (2024, March). Human skills in the era of industry 4.0 in the Indian automotive industry. *Abhigyan*, *42*(2), 123–144. https://doi.org/10.1177/09702385241235459

Tervo, K., Palmroth, L., & Koivo, H. (2010). Skill evaluation of human operators in partly automated Mobile working machines. *IEEE Transactions on Automation Science and Engineering*, *7*(1), 133–142. https://doi.org/10.1109/TASE.2009.2025364

Wright, T. P. (1936). Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences*, *3* (4), 122–128. https://doi.org/10.2514/8.155

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and industry 5.0—inception, conception and perception. *Journal of Manufacturing Systems*, *61*(October), 530–535. https://doi.org/10.1016/j.jmsy.2021.10.006

Zhao, W., Pu, S., & Jiang, D. (2020). A human resource allocation method for business processes using team faultlines. *Applied Intelligence*, *50*(9), 2887–2900. https://doi.org/10.1007/s10489-020-01686-4