Exploring Learning-Forgetting Models: A Comprehensive Taxonomy Investigating Activities-Related Features in Different Working Scenarios

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Abstract: The worker-related phenomenon of learning and forgetting has received a significant attention in several fields of study. It is important to understand how individuals acquire, maintain, and potentially loose competence to optimize training strategies and performance outcomes, posing challenges and opportunities for both researchers and practitioners. This study explores the use of learning and forgetting models in manufacturing, assembly, maintenance, and logistics considering specific task features such as work environment as well as nature, frequency, difficulty, and criticality. Results of the taxonomy show that there is a significant research gap on learning-forgetting models regarding cognitive activities, as well as non-routine activities, or tasks characterized by a high level of criticality. Due to the technological advancements of the last years, there is a progressive transition from repetitive motor activities to tasks that require more cognitive efforts, characterized by higher complexity, and lower level of repetitiveness. Understanding the nuances of forgetting can aid in developing more effective training and knowledge retention strategies, thereby enhancing performance and well-being of workers. Therefore, there is an increasing need to study learning and forgetting phenomena focusing on the new type of activities emerging in the current working scenarios.

Keywords: 'Learning and Forgetting', 'Training strategy', 'Cognitive task'

1. Introduction

In recent decades, the industrial landscape has undergone a significant transformation due to the common adoption of advanced digital technologies and the convergence of physical and digital systems. The transformation process is commonly associated with the concept of 'Industry 4.0'. This paradigm is characterized by the integration of smart technologies, the automation of production processes, and the creation of interconnected systems that enable real-time data collection and analysis (Zizic et al., 2022). Although Industry 4.0 (I4.0) has led to significant increases in efficiency, productivity, and flexibility in industrial processes, we are now witnessing a new evolutionary phase: Industry 5.0 (I5.0).

I5.0 is the next stage in the transformation of the industrial sector, with a greater emphasis on human-machine interaction, collaboration between robots and human operators, and the integration of advanced technologies such as artificial intelligence, collaborative robotics, and the Internet of Things (Zizic et al., 2022). I5.0 poses its emphasis on creating resilient, sustainable, and human-centric working environments (Facchini et al., 2021; Ferrante et al., 2024).

The transition from I4.0 to I5.0 presents unique challenges and opportunities for individuals, organisations, and technologies involved in the production process. A crucial aspect of this transition concerns the nature of tasks required to operators. Industry 5.0 requires adaptation to current working scenarios where tasks become more varied and complex (Goos et al., 2014). Recent studies highlight job polarisation, with an increasing demand for high-skilled jobs that require advanced cognitive skills, and a decrease in low-skilled jobs that are threatened by routine-biased technological change and offshoring (Arregui Pabollet, E. et al., 2019). Moreover, digitization and automation are transforming the nature of work, demanding skills that go beyond technical abilities, such as problem-solving, creativity, and adaptability (Davis et al., 2017).

While many organizations recognize the need for further training, manufacturers aim to reduce costs by developing efficient and concise learning methods. To achieve this goal, an alternative approach is required that encourages proactive learning among trainees. This paradigm reduces training duration, improves skills retention, cultivates situational awareness, and contributes to a healthier and safer working environment (Matyas et al., 2017).

However, despite extensive discussion on the evolution of the industry and its implications for work, there is a noticeable gap in the literature.

Specifically, there is a significant lack of works dedicated to the new training needs in the context of Industry 5.0. This study investigates the causes of this gap through a taxonomy of works that deal with learning-forgetting models, posing emphasis on activities-related features such as level of criticality, frequency, nature and complexity of tasks. The goal is to guide future engineers and managers in the optimal design of learning and training strategies that consider new needs and challenges posed by Industry 5.0.

The article will follow this structure: Section 2 provides background on learning and forgetting models. Section 3 examines proposes the taxonomy of works related to learning and forgetting by considering type of application, type of task, frequency, criticality, and difficulty. Sections 4 and 5 present discussion and conclusions.

2. Background

The Wright curve, also known as the learning curve or experience curve, is a fundamental concept in the field of operations management and industrial optimization. It was first introduced by Theodore Paul Wright in 1936 during his studies on aircraft production in World War II (Wright, 1936). This theory has found common applications in various fields, including industrial production and innovation industries.

The intrinsic relationship between the experience gained in a particular activity and the productivity achieved over time is the essence of this concept. As experience is gained, performance tends to improve in a measurable and predictable way. Productivity often increases exponentially as experience and skills improve, procedures are optimized, and resources are managed more efficiently. Wright's curve illustrates this phenomenon by demonstrating the relationship between productivity and the number of iterations or experience accumulated. This idea has been and continues to be an essential tool for companies to understand and manage learning and improvement processes. By doing so, companies can more effectively plan staff training, optimize production processes, and set realistic expectations for delivery times and costs (Kim et al., 2013).

Wright's learning model has undergone refinements and extensions through the development of innovative models and approaches. These models aim to refine the understanding of the relationship between experience and productivity to apply this concept in complex and dynamic contexts as well as to overcome some limits of the Power model of Wright.

Further phenomena causing dynamic variability of workers' performance have been investigating since the previous century. Jaber and Bonney (1996) proposed a 'learning-forgetting' model allowing to consider the opposite effect of non-working time on learning. More recently, Podolski et al. (2022a) investigated the impact of learning and forgetting processes on construction project costs. In (Jaber et al., 2013), Authors investigated on the effectiveness of learning in workers subjected to fatigue phenomenon. Additional contributions to this topic is provided in (Asadayoobi et al., 2021a), where Authors proposed a fatigue level-dependent learning rate for order-picking tasks.

In the context of task planning optimization, numerous scholars have proposed innovative models and algorithms to address specific challenges in manufacturing. For instance, Morimoto et al. (2016) presented a model based on constrained cellular automata with the aim of lean manufacturing of carbon fiber aerospace components. This model aims to optimize manufacturing processes by exploiting learning curve principles, thus enabling significant improvements in operational efficiency. Similarly, Sekkal and Belkaid ((2023) address the challenge of planning production activities by considering both setup time and worker learning processes through multi-objective optimization. These approaches provide a comprehensive framework for addressing the complexities of production activity planning, enabling optimal resource utilization and overall efficiency. Concurrently, Liu et al. (2016) examine learning and improvement processes in organizations, offering a more comprehensive analysis. Building upon this foundation, Kiomjian et al. (2020) investigate the relationship between knowledge sharing and organizational productivity. Understanding the impact of knowledge sharing on business performance is essential for developing effective optimization strategies. In a recent publication, Szwarc et al. (2024) offer further insights into the processes of learning and improvement within organizations. This research helps to delineate the internal dynamics of companies and enables the development of more targeted strategies to optimize overall performance and achieve business goals. Optimization of production and maintenance processes plays a pivotal role in ensuring operational efficiency and end-product quality. Tarakci (2016) examined the influence of learning on maintenance activities over time, providing a distinctive perspective on maintenance process optimization. Understanding how learning affects maintenance activities over time is of paramount importance for developing effective strategies to maximize equipment reliability and minimize downtime. Furthermore, Chu et al. (2019) proposed a model that considers machine degradation, human errors, and their effects on production processes. Including these factors in the production model allows for anticipation and proactive management of unforeseen events, thus ensuring the continuity of operations and product quality. Several studies have emerged that address the challenges associated with the complexity of production processes and personnel management. Kataoka et al. (2019) emphasised the continued importance and relevance of Wright curve theory in the context of manufacturing in industrial settings. Recently, Ranasinghe et al. (Ranasinghe et al., 2024) proposed a model that deals with stochastic and heterogeneous learning of workers. This model considers individual variations in learning processes, enabling more effective human resource management and higher overall productivity. In addition, recent studies have expanded our understanding of workforce management and learning dynamics within organizations. Cavagnini et al. (addressed variability in learning rates, highlighting the importance of robust workforce planning strategies. Ostermeier and Deuse (2023) examined the phenomenon of forgetting in intermittent manufacturing environments, shedding light on the challenges and opportunities associated with managing memory decay in manufacturing environments. Other researchers, such as Korytkowski (2017) and Hoedt et al. (2019), have contributed to the field with their innovative models and approaches. These collective efforts enhance our ability to develop targeted strategies to optimize manufacturing activities and workforce management, ultimately leading to increased productivity and achievement of organizational goals.

3. Taxonomy of learning-forgetting models

To define a taxonomy of learning-forgetting models, relevant scientific papers on this topic have been retrieved from Scopus database and analysed. The search has been carried out using string obtained combining words 'learning', 'forgetting', 'rate', 'curve', process', 'model', 'manufacturing', 'industry', 'maintenance', 'operator', 'worker', 'workforce', 'employee'. Papers published in English from 2009 in both journals and conference proceedings have been considered. The selection process included an initial screening of titles and abstracts to identify relevant articles, followed by a full-text review to assess the relevance and quality of the studies. Specifically, we included documents that discuss the impact of learning and training in the context of Industry 4.0 and, where present, Industry 5.0. We ensured a satisfactory level of comprehensiveness by considering studies from various disciplines and industrial applications, thus covering a broad spectrum of approaches and model. In the following, only most relevant papers are discussed to support the taxonomy proposed. They have been classified according to the following tasks features: application field, type of activity and task frequency, criticality, and difficulty, as detailed in Appendix A and discussed in the following. As showed in Appendix A, in all the papers considered a new or the application of an existing learning model is discussed. In some of them, also forgetting phenomenon is considered.

3.1 Feature A: Work environment

Work environment refers to the type of activity for which the models or the applications proposed by Authors have been defined and/or applied. In most of the papers considered, learning and forgetting models/applications refer to tasks related to production activities. Few papers deal with maintenance (Szwarc et al., 2024; Tarakci, 2016) and order picking (Loske and Klumpp, 2020) ones.

As highlighted by Z. Luo et al (2022), the learning and forgetting curve are a fundamental concept with numerous cross-sectional applications in sectors such as production and maintenance. In production contexts, understanding these phenomena can allow for efficient planning of employee training activities, thus improving overall productivity. In maintenance, the analysis of the learning and forgetting curve can help optimize preventive maintenance strategies and predict equipment replacement times, reducing costs, and improving plant reliability (Luo and Su, 2022).

3.2 Feature B: Task nature

Papers have been further classified based on the nature of the tasks (motor/cognitive), models or applications provided are conceived for. Motor tasks mainly involve tasks such as handling items or assembling components. On the other hand, cognitive activities mainly involve mental processes such as problem-solving, data analysis, and strategic planning.

Models and applications in the papers considered mainly focus on motor tasks. In (Morimoto et al., 2016), a learning curve for carbon fiber component production tasks is proposed; learning and forgetting phenomena in garment production tasks are considered in (Badri et al., 2016; Ranasinghe et al., 2024); assembly tasks are considered in (Mark et al., 2020); manual pick-by-voice and semi-automated order picking tasks are considered in (Loske and Klumpp, 2020); activities in the construction sector are addressed in (Podolski et al., 2022a); maintenance tasks are considered in (Tarakci, 2016). Szwarc et al. (Szwarc et al., 2024), focus on cognitive tasks carried out by multi-skilled IT programmers.

3.3 Feature C: Task Frequency

A further classification concerns the frequency of the execution of the task investigated in the papers considered. Papers have been clustered into three classes: (i) high, if the task investigated is performed at least once during the work shift; (ii) medium, in case the task occurs at least once per month; (iii) low, in case of a frequency less than once a month.

High frequency tasks performed in production/assembly environment are common in the paper considered as in (Ranasinghe et al., 2024; Che et al., 2022 Chu et al., 2019). In contrast, Hakan Tarakci (2016) discusses maintenance, specifically preventive maintenance (PM), where a lower frequency of task execution (quarterly or semi-annually), is required. In case of corrective maintenance, no specific frequency is identified since it is implemented in response to a specific failure. Not all papers considered have been classified based on this feature due to the unavailability of data on tasks frequency.

3.4 Feature D: Task Difficulty

The fourth feature considered is task difficulty. Currently, there is not a wide consensus on how to measure task difficulty (Liu and Li, 2012). In this paper, the task's level of difficulty is assessed based on three main factors.

The first factor considered is the task execution frequency. A high frequency can increase the task complexity perceived by the worker and, consequently, its level of difficulty. As second factor, we considered the expected duration of the task. Tasks that take a long time tend to be more complex to manage and complete, which can affect their difficulty. Finally, the last factor considered is the knowledge required to effectively perform the task. Tasks that require specialized training or extensive experience may be more demanding. By considering these factors, three task difficulty levels are identified: high, medium, and low, in case of 3 out of 3, 2 out of 3, and 1 out of 3 factors assume high values, respectively. In the reviewed papers. a variety of difficulty levels were found.

Tasks with a high level of difficulty are considered in (Che et al., 2022; Zhang et al., 2022), where critical variables such as machine degradation, which inevitably affects operator learning, can be difficult to manage. Similarly, variables such as machine set-up times can increase the level of difficulty, as they require efficient management by the operator. For instance, construction projects require familiarity, as discussed in (Podolski et al., 2022a). Tarakci (Tarakci, 2016) highlights that unexpected maintenance tasks require a high level of alertness and responsiveness, as the operator must be ready to intervene without continuous preparation on the machines used. These tasks are found to be more difficult compared to others. Case studies involving multi-skilled operators, who must be versatile as they deal with a wide range of tasks requiring both motor and cognitive involvement, also fall into the high level of difficulty (Chu et al., 2019; Hoedt et al., 2019; Liu et al., 2016).

In case of tasks performed with low frequency but requiring not only motor effort, but also in-depth knowledge of production dynamics, material properties, and their applications, medium level of difficulty is assigned (Morimoto et al., 2016).

In contrast, items with a low level of difficulty are also investigated, such as in order picking systems, particularly those incorporating audio (Loske and Klumpp, 2020) or video support, which reduces operational complexity and facilitates task execution (de Giorgio et al., 2022).

3.5 Feature E: Task Criticality

The last feature considered is the task criticality; it is based on three factors. Two of them (safety issues and economic issues) are evaluated based on the outcomes that can occur in case the task is not performed, or it is not performed in the proper way; the last factor considered is the task execution frequency (the more a task is performed, higher will be the occurrence probability of a missed or an improper execution). Based on above mentioned factors, papers were classified into three criticality levels: high, medium, and low, by adopting the same classification criteria of feature D.

Many of the reviewed studies concentrate on high critical tasks as in the case of critical components for airplane structures, since errors in this area can affect flight safety (Morimoto et al., 2016). Che's perspective (2022) on the effects of machine degradation on operator learning and the associated high risk is of particular interest. The construction sector has experienced significant challenges (Ergun and Pradhananga; Podolski et al., 2022a). These challenges arise not only from the nature of the work, but also from the high number of repetitive tasks that are typical in this industry.

The production in textile industries can present medium critical tasks, as shown in (Badri et al., 2016). Tasks with low criticality were found also in production contexts(Cavagnini et al., 2020; Hoedt et al., 2019; Liu et al., 2016; Mark et al., 2020; Ostermeier and Deuse, 2023).

Not all tasks investigated in the reviewed papers exhibit high or medium criticality. In fact, new technologies have been introduced to assist operators during work activities, particularly in the field of production. For instance, Loske et al. (2020) investigated semi-automated picking in production, utilizing 'pick by voice' and 'pick by light' modes. Additionally, a recent study on learning using explanatory videos (de Giorgio et al., 2022), has shown that expert video assistance accelerates initial assembly learning, but presents challenges due to data variance. Unassisted operators demonstrate slower but significant improvements in long-term learning, which requires the attention of both industry and researchers. In these cases, the resulting criticality can be classified as low.

4. Discussion

Understanding how the dynamics of learning and forgetting influence job performance is crucial for driving innovation and growing in an industrial world that is constantly changing. By combining the various criteria used for classification, we can identify key areas that require further exploration and consideration to effectively address the evolving needs of modern industrial operations. In Table 1 main findings on the present article have been summarized.

A significant observation that emerged from the review is the bias in research on the learning effect in cognitive tasks. While the reviewed literature mainly focuses on learning-forgetting models in motor tasks such as production and maintenance, there is a lack of studies on cognitive tasks.

Table 1 Features and main findings related to Learning-Forgetting Models

Feature	Main Findings
Task Nature	Most models focus on motor tasks like handling items or assembling components. However, cognitive tasks are crucial for Industry 5.0 and require more attention.
Task Frequency	High frequency tasks are performed daily and are common in production settings. Lower frequency tasks, like preventive maintenance, are less frequent. Not all studies provide data on task frequency.
Task Difficulty	Difficulty is assessed by task frequency, duration, and required knowledge. High difficulty tasks involve complex variables like machine degradation. Medium difficulty tasks require specific knowledge. Low difficulty tasks are simpler.
Task Criticality	Criticality is based on safety, economic impact, and frequency. High criticality tasks are common in high-risk sectors like aviation and chemical industry. Medium and low criticality tasks are also present in production contexts.
Work Environment	Learning and forgetting models are mainly applied to production tasks, with fewer studies on maintenance and order picking. Understanding these models helps to optimize training and maintenance strategies.

This gap becomes particularly relevant in the transition to Industry 5.0, where human-machine collaboration and cognitive skills are increasingly important. These skills are essential in contexts where collaboration between humans and machines is increasingly integrated, such as in complex decision-making processes or in the interpretation and analysis of data, to ensure accurate and effective results. In Industry 5.0, where customization and adaptability are crucial, the ability to solve complex problems, innovate, and quickly adapt to market changes is essential for business success. Investing the cognitive skills of operators enables companies to tackle more complex challenges and seize emerging opportunities more effectively.

The task frequency classification criterion emphasizes the prevalent focus on repetitive and routine tasks. However, as industries advance towards Industry 5.0, characterized by greater flexibility and personalization, tasks become more varied and dynamic. To maintain high standards of productivity and quality, operators must learn quickly and adapt effectively to new situations and tasks. Preparing operators for this increasing variety and complexity is essential. Investing the cognitive skills of operators can enhance a company's efficiency, innovation, and competitiveness, preparing them for an increasingly digitized and dynamic industrial future.

The assessment of task difficulty highlights the multifaceted nature of the challenges faced by operators in modern industrial settings. As tasks become more complex in Industry 5.0, there is a growing need for adaptive learning approaches that consider individual learning styles and preferences. Customized learning solutions allow operators to acquire skills more effectively by focusing on their specific strengths and areas for improvement. By utilizing emerging technologies, such as virtual reality simulations and augmented reality assistance (Longo et al., 2023), training can be enhanced by providing immersive and interactive learning experiences. The adoption of adaptive training approaches and the use of innovative technologies can play a key role in preparing operators for the challenges of Industry 5.0. Investing in advanced training solutions improves operators' skills and fosters a safe, efficient, and state-of-the-art working environment.

It is important to consider not only productivity implications but also safety and economic factors when assessing the criticality of tasks. Tasks with high criticality require more attention in training and skills development efforts to mitigate risks and prevent costly disruptions. In Industry 5.0, the criticality of tasks may evolve as the interaction between humans and machines becomes increasingly integrated. Therefore, it is important to continuously adapt strategies for managing and mitigating risks associated with critical tasks to align with evolving technological developments and operational paradigms. In Industry 5.0 while some tasks may become less critical due to the increased reliability and automation of processes, others may become more critical due to the complexity of human-machine interactions. For instance, the introduction of collaborative robots in production lines may reduce the criticality of repetitive and physical tasks but may increase the criticality of maintaining and programming the robots themselves.

The criticality assessment of tasks may be affected by the working environment. Sectors with high risks, such as the chemical industry, nuclear energy, or aviation, may have a higher concentration of highly critical tasks than less hazardous sectors, such as the service sector. Therefore, it is necessary to tailor training and risk management strategies to the specific operational context. Assessing the criticality of tasks in Industry 5.0 requires a comprehensive approach that considers not only productivity but also safety, cost-effectiveness, and technological developments. In-depth analysis and proactive risk management are necessary to ensure a safe, efficient, and state-of-the-art working environment.

From a practical perspective, analyzing the taxonomy of learning-forgetting models provides valuable insights into how companies can optimize their training and competence development strategies to meet the challenges of Industry 5.0. It is crucial to invest in training programs that focus not only on technical skills but also on the cognitive and adaptive skills required. To improve the skills of employees, ad hoc training courses should be introduced to encourage the development of problem-solving, creativity, and adaptability, in addition to technical knowledge. Moreover, companies should promote flexible training programs that enable operators to acquire skills efficiently and effectively to cope with the increasing variety, complexity, and frequency of tasks. Companies must ensure that operators are adequately trained to handle emergency situations and prevent accidents in the workplace, given the potentially serious implications of errors in critical activities such as maintenance of plants. The use of virtual simulations, augmented reality, and game-based learning can make the training experience more engaging and interactive, enabling operators to acquire skills more effectively and memorably. By adopting a holistic approach to train and develop innovative and adaptable strategies, organizations can ensure that their teams are equipped to meet the challenges and seize the opportunities presented by this new industrial paradigm. Furthermore, the strategic application of learning and forgetting models can enhance an organization's resilience, allowing for more effective management of critical competencies during crises and periods of rapid technological or market changes. These models facilitate organizational adaptability to new technologies, helping employees continuously maintain and update their skills, which is crucial for competing in the era of Industry 5.0.

5. Conclusion

Despite the progress made in understanding the dynamics of learning and forgetting, there is a clear gap in the literature regarding training needs and strategies specifically adapted to I5.0. This gap highlights the need for innovative approaches that address the changing landscape of industrial activities, characterised by digitisation, cognitive, and less repetitive activities. To fill this gap and pave the way for future developments, it is essential to propose new models that represent a paradigm shift in the training of operators.

These models should be designed to efficiently address the identified gaps while ensuring economic sustainability. Training models should be optimised to deliver effective results in a short period of time while minimising costs. Innovative training methods, such as adaptive learning algorithms and customised learning paths, can help achieving this by tailoring the learning experience to the individual needs and capabilities of participants. While reducing training time is essential, it is equally important to ensure the effectiveness of training in providing practitioners with the necessary skills and knowledge.

Therefore, interactive learning tools, practical simulations and real-life scenarios should be integrated into the training phase to improve retention and application of skills. At the same time, it is crucial to ensure the safety of operators during training, especially in areas with high-risk activities. It is therefore necessary to integrate safety protocols, emergency response simulations and risk management strategies to prepare operators for potential workplace hazards, minimising the risk of accidents or injuries. Given the dynamics of I5.0 work environments, integrating these principles into the training models will not only fill existing knowledge gaps, but also enable organisations to keep pace with the rapidly changing industrial landscape.

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Appendix A.

List of articles analysed. Abbreviations: MA = Maintenance; PR = production; OP = order picking; C = cognitive task; M = motor task; L = low; M = medium; H = high; n.a. = not available

Reference	Learning	Forgetting	Work environment	Task nature	Task Frequency	Task Difficulty	Task Criticality
(Szwarc et al., 2024)	✓	✓	MA	C	H	M	L
(Ranasinghe et al., 2024)	✓		PR	M	H	M	H
(Sekkal and Belkaid, 2023)	✓		PR	M	H	H	H
(Ostermeier and Deuse, 2023)		✓	PR	M	H	H	M
(Luo and Su, 2022)	✓	✓	n.a	n.a	n.a	n.a	n.a
(Podolski et al., 2022b)	✓	✓	PR	M	H	H	H
(Che et al., 2022)	✓	✓	PR	M	H	H	L
(de Giorgio et al., 2022)	✓		PR	M	n.a	L	L
(Zhang et al., 2022)	✓	✓	PR	M	H	H	H
(Asadayoobi et al., 2021b)	✓		PR	M	H	L	L
(Mark et al., 2020)	✓		PR	M	H	M	M
(Kiomjian et al., 2020)	✓		PR	M	H	M	H
(Cavagnini et al., 2020)	✓	✓	PR	M	H	L	M
(Loske and Klumpp, 2020)	✓		OP	M	H	L	L
(Chu et al., 2019)	✓	✓	PR	M	H	H	H
(Hoedt et al., 2019)		✓	PR	M	n.a	H	M
(Kataoka et al., 2019)	✓	✓	PR	M	H	H	H
(Korytkowski, 2017)	✓	✓	PR	M	n.a	M	L
(Tarakci, 2016)	✓		MA	M	L	H	H
(Liu et al., 2016)	✓	✓	PR	M	H	H	M
(Badri et al., 2016)	✓		PR	M	H	L	M
(Morimoto et al., 2016)	✓		PR	M	H	H	H
(Kim et al., 2013)	✓	✓	n.a.	n.a	n.a	n.a	n.a
(Jaber et al., 2013)	✓	✓	PR	M	n.a	M	L