

# **AUTODIDACT: INTRODUCING THE CONCEPT OF MUTUAL LEARNING INTO A SMART FACTORY INDUSTRY 4.0**

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## **ABSTRACT**

This paper explores the concept of mutual (reciprocal) learning as an enabler of the emergence of a collective human-machine intelligence across a smart factory. The interlinking of digital profiles of humans and machines permits the identification and measurement of learning outcomes through participating in and performing of (shared) tasks. To achieve this goal and ultimately to transform today's smart factory into a self-learning factory, the concept model of AUTODIDACT, underlying objectives and research questions related to mutual (reciprocal) learning are outlined.

## **KEYWORDS**

Human Learning, Machine Learning, Human-Machine Interaction, Hybrid Learning, Industry 4.0, Collective Intelligence

## **1. INTRODUCTION**

A trendy topic in the research area of human-technology interaction at the workplace is job automation. Modern factories and the vision of Industry 4.0 inevitably lead to higher automation and a decreasing number of direct personnel in factories. However, the recent European skills and jobs survey (Cedefop, 2018), which comprises a large body of studies, doubts the significance of the predictions with regard to the robotization of the labor market. The main reason for imperfect predictions is grounded in the market, industry sector or technology specificity of the hypotheses, which affects the formulation of theory and accordingly proper explanation and interpretation of a set of phenomena. At the same time, the survey reveals that the march of technological progress may widen inequality, e.g. with regard to wages and contribute to the polarization of jobs in the labor market (Cedefop, 2018). Evidently, the automation of jobs and firms reliance on robots are highly correlated (Acemoglu & Restrepo, 2017).

Over the past decades, the reliance of European companies on robots has been increasing from 0.6 robots per 1,000 workers in 1990s to 2.6 robots per 1,000 workers in the late 2000s (Acemoglu & Restrepo, 2017), where robots have primarily replaced low-medium skilled workers carrying out manual and repetitive tasks rather than critical, non-routine or decision-making tasks. As a result, there is less opportunity for human learning, in particular for low-medium skilled workers, resulting in decreasing tacit knowledge about processes and systems. This effect was described 35 years ago as one of the "ironies of automation" (Bainbridge, 1983) and "recent technological developments may have some new ironies in store for us" (Baxter et al., 2012). Such recent technological developments include robotics and (intelligent) assistance systems as well as the possibilities of distributed Internet of Things (IoT)-applications, artificial intelligence and machine learning, which are some of the driving forces behind Industry 4.0. However, in all the excitement about the new technological potential with respect to automation and digitalization, human capabilities are often considered as a given, almost static variable. In an extension of the "human-in-the-loop" approach, this paper presents a mutual (reciprocal) learning methodology to human-machine learning with the goal, to improve the capabilities of both humans and machines simultaneously in order to raise their "Collective Intelligence" (Levy, 1994; Glenn, 2013).

Reframing the risks of automation as an opportunity, the key research question is “How to build an integrated human-machine collaboration framework for mutual learning in smart factories?”, based on the definition of mutual learning (also known as human-machine reciprocal learning) given by (Ansari et. al., 2018a). Foresight involves future-oriented awareness in order to enable today’s smart factories to transform into human-centered self-learning factories. To this end, Section 2 discusses learning in smart factories under consideration of background terminologies, challenges and requirements from both technological and non-technological perspectives. Furthermore, it discusses the concept of mutual learning and introduces related terms such as “human and machine as a learner” in smart factories. Accordingly, Section 3 presents the AUTODIDACT concept for building a mutual learning platform in TU Wien’s Pilot Factory Industry 4.0. Finally, Section 4 concludes the discussion and elaborates on a future research agenda.

## 2. REQUIREMENTS AND CHALLENGES FOR LEARNING IN SMART FACTORIES

### 2.1 Smart Factories: Terminology and Background

Advances in collaborative robotics and data science are expected to lift factory automation to a new level (IFR, 2017; Bauer et al. 2016; Monostori et al. 2016). Together with the widespread use of IoT technologies within manufacturing facilities, their implementation is widely referred to as “smart factory” (Zühlke 2008, Kagermann et al. 2013; Wagner et al., 2017). The vision of Industry 4.0 advocates the realization of smart factory technologies to connect humans, machines and intelligent objects in order to create high-performance processes and products (Spath, 2013; Liao et al., 2017).

Traditionally, automation and Industry 4.0 tend to emphasize technological opportunities and focus less on the organizational setting and socio-technical environment. In order to tap the full potential of Industry 4.0 and to create a conducive environment to test new approaches in human-machine learning, it is necessary to employ a comprehensive approach that takes well-known interdependencies of factories, as socio-technical entities with strong interdependencies between technological and organizational changes, into account.

It is already visible, that the transformation with regard to the integration of new technologies will have significant effects on the way manufacturing is organized. The increasing degree of autonomy of intelligent robots and assistance systems poses a major challenge to the traditional organization of factories. Collaborative and mobile robotics will carry out manual routine tasks, while digital assistance systems take over cognitive routine tasks and provide support in non-routine situations. Consequently, the organization of work will inevitably change and autonomous systems increasingly require human work that is more flexible. The required competences of factory workers as well as those of support functions such as maintenance and quality assurance staff, are expected to change significantly (Jaeger et al. 2012; Erol et al. 2016; Lanza et al. 2016).

### 2.2 Learning Matters in Smart Factories

As the expected changes in competency development due to Industry 4.0 are widely discussed, there is a need to establish processes to adapt learning in a factory environment to those changes, in order to retain and improve learning curves for blue-collar and white-collar employees. Due to increased automation in smart factories, the challenges of learning grow on various levels. The barriers (challenges) to learning in smart factories comprise the following:

- **Larger scope:** Due to higher automation and increasingly autonomous technical systems, the average staffing per machine decreases. Hence, the number of processes, to be mastered by the remaining employees, is increasing.
- **Fewer learning opportunities:** Due to the fact, that machines take over routine tasks and the resulting focus of humans is put on non-routine tasks, less learning opportunities with respect to routine processes exist for human operators (Baxter et al., 2012).
- **Uncertain role of human work in hybrid (human-machine) settings:** Due to collaborative tasks with machines and algorithms, additional requirements in terms of learning emerge. Especially the

“reciprocal learning approach” will become necessary in hybrid (man-machine) settings in a smart factory. This approach uses human experience and tacit knowledge to train machine data sets (machines learn from humans) and on the other hand employs data-based learning that is guided by smart algorithms (humans learn from machines) (Goldberg, 2017).

Besides the challenges mentioned above, learning in a smart factory also changes its perspective with regard to different periodicity.

- **Short-term:** The need for process optimization, operational excellence and quick results usually drives learning in the short-term. To learn how to carry out one or several work tasks more efficiently, usually follows a learning curve (Zangwill, 1998) and short-term learning goals translate into a steepening of the learning curve during the ramp-up phase.
- **Mid-term:** With the emergence of hybrid settings of mixed man-machine teams, there is a need for an optimal assignment of tasks in order to guarantee a good fit with the team members. The assignment of tasks depends on the individual capabilities and the needed effort to train each team member for a specific task. Moreover, task assignment is most likely not static and will change over time as the capability level of workers and machines evolves. Hence, there will be a constant need for training and retraining and task assignment will be evaluated with respect to relevant parameters such as economic and organizational goals, but also regarding competency development and learning.
- **Long-term:** Learning about and gaining an understanding of a manufacturing process usually contributes to process and product innovations. Mistakes, mishandling and unplanned events regularly offer room for small improvements or even novel ideas. Furthermore, the tacit knowledge of processes and their interconnections and eventual impacts provide a competitive advantage that is often hard to copy. Therefore, the optimal ratio of automated and human decision-making is essential in maintaining an organization’s ability to improve and adapt to unplanned and to some extent unforeseeable changes.

### 2.3 Human and (Intelligent) Machines as a Learner in Smart Factories

Considering the technological advancements in smart factories, the division of tasks between human workforces and machines is changing from distinctive roles and tasks into hybrid (collaborative) roles and task schemes. The latter divides the entire pool of tasks into three clusters, namely; i) tasks assigned to the human workforce, ii) tasks assigned to (intelligent) machines, and iii) shared tasks assigned to both human workforce and intelligent machines (including robots in particular collaborative robots (cobots), virtual assistance systems, etc.) (cf. Figure 1).

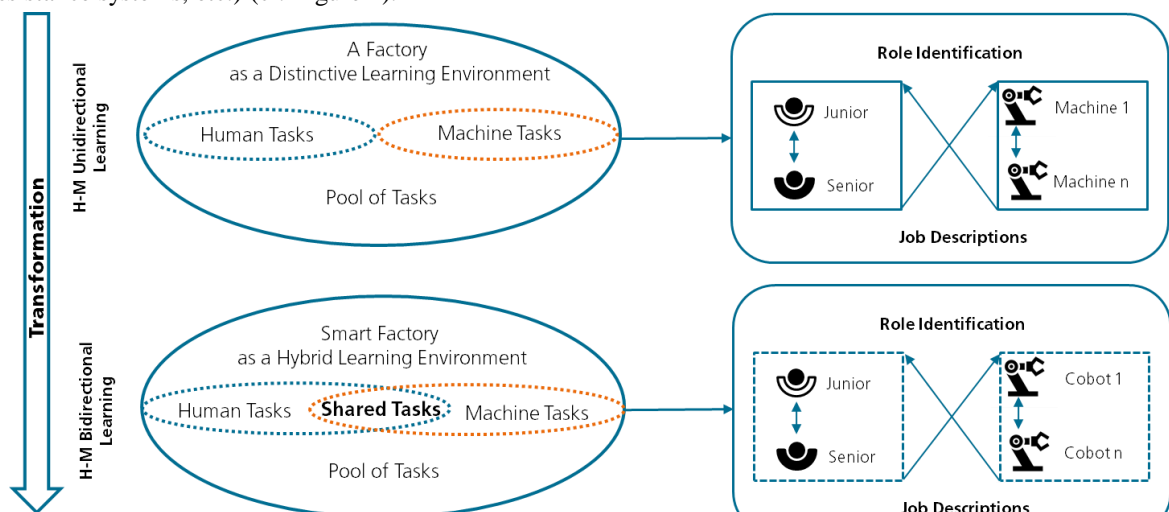


Figure 1. Division of tasks and its impact on human-machine learning

Participation in the shared tasks necessitates the learning capabilities of human workforce and machines (i.e. humans and machines as a learner) and further combines them into a new boundary system in which mutual learning takes place. Here, we slightly modify the definition of human-machine mutual learning given

earlier by (Ansari et al., 2018a) as follows: «*Mutual learning is a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating a new meaning or concept, enriching the existing ones or improving skills and abilities in (symmetric or asymmetric) associated with each group of learners*».

Creating digital profile of the aforementioned group of learners facilitates modeling, estimating and evaluating the exact magnitude and significance of the learning effectiveness and outcomes resulting from mutual learning in smart factories. Furthermore, digital profiles of human workforces and machines provide possibilities to collect data, construct distinct learning profiles and identify mutual learning in a consistent, dynamic and realistic way. A digital profile typically comprises all basic information, i.e. personal or professional information of a human workforce or technical specifications of a machine. It also contains on-the-job performance data collected by means of sensors and condition monitoring systems for the target human workforce or machine as well as feedback collected e.g. via a 360°-feedback (multi-source feedback) approach, or via a customer or end-user questionnaire survey. Such a continuously growing database provides opportunities for identification and prediction of learning trajectories for both human and machine workforces over time.

The machine's digital profile can be quantified based upon the determination of the degree of autonomy of the individual machine functions. The degree of autonomy of a machine specifies its technical ability to autonomously adapt to dynamically changing production conditions, without endangering the efficiency and effectiveness of the production process. In order to define the degree of autonomy of a machine, a descriptive basis for a corresponding comparison must first be determined. There are various possibilities for this corresponding comparison, e.g. as proposed by (Gronau & H. Theuer, 2016):

- i) [Number of autonomous functions / number of all functions],
- ii) [Number of autonomous controlling systems / number of all controlling systems],
- iii) [Number of autonomous actuator systems / number of all controlling actuators],
- iv) [Number of autonomous resource supply systems / number of all resource supply systems],
- v) [Number of autonomous mobility systems / number of all mobility systems], and
- vi) [Autonomous quantity of data / total quantity of data].

The degree of autonomy shall be determined for each machine function. A summation of the corresponding quantified degrees via Likert scaling enables the definition of a specific machine's digital profile, which can be described in the form of a vector representation.

Furthermore, the concept of machine's digital profile may resemble the virtual representation, monitoring and configuration of a machine's components and functions in a dynamic manner. Therefore, the term Digital Twin is defined as an evolving digital profile of a production system (Brenner & Hummel, 2017). It establishes an interface between the physical and digital world through streaming and linking the status data of all physical objects in the production system to their virtual models (Uhlemann et al., 2017). Using intelligent data analytic methods, learning accomplishments can be recorded and corresponding implementation decisions can be directed to operators and technical systems (Mussomeli et al., 2017). In the proposed concept of AUTODIDACT, the term Machine Digital Twin is used to address the digital profile of a machine workforce (cf. Section 3).

The definition and characteristics of the Human Digital Profile are based on descriptive parameters consisting of different determinants, which enable a human workforce to perform a task in a work system. According to (Schlick et al., 2010) these determinants include i) human constituent characteristics, ii) human disposition characteristics, iii) human qualification and competency characteristics, and iv) human adaptation characteristics. Employing "Performance Shape Factors 3" (PSF 3) introduced by (Bubb, 2005), it is possible to build a quantified human digital profile as discussed in (Ansari et al., 2018b).

Human- and machine's digital profiles are the core building blocks for realizing an integrated human-machine collaborative framework for mutual learning in smart factories, which is discussed in Section 3.

### 3. AUTODIDACT - TOWARDS MUTUAL LEARNING IN TU WIEN'S PILOT FACTORY INDUSTRY 4.0

The TU Wien Pilot Factory Industry 4.0 (PFI4.0) is a research lab and demonstration factory for promoting the realization of smart factory technologies – tailored to the future-oriented solutions for manufacturing industries (PFI40, 2018; Ansari et al., 2018a). Human-technology collaboration is one of the main problem areas in which the current focus is on realizing innovative solutions for human and technology interactions, including human-robot collaboration, digital assistance systems, etc. Such solutions aim at enhancing workplace productivity and efficiency, and improving working conditions and safety. As discussed earlier, learning is the key to innovation. In particular, mutual learning is essential to develop and enhance synergistic innovation capability in the PFI4.0. Hence, the concept of “AUTODIDACT” envisages an integrated human-machine collaboration framework for mutual learning in the PFI4.0 (cf. Figure 2).

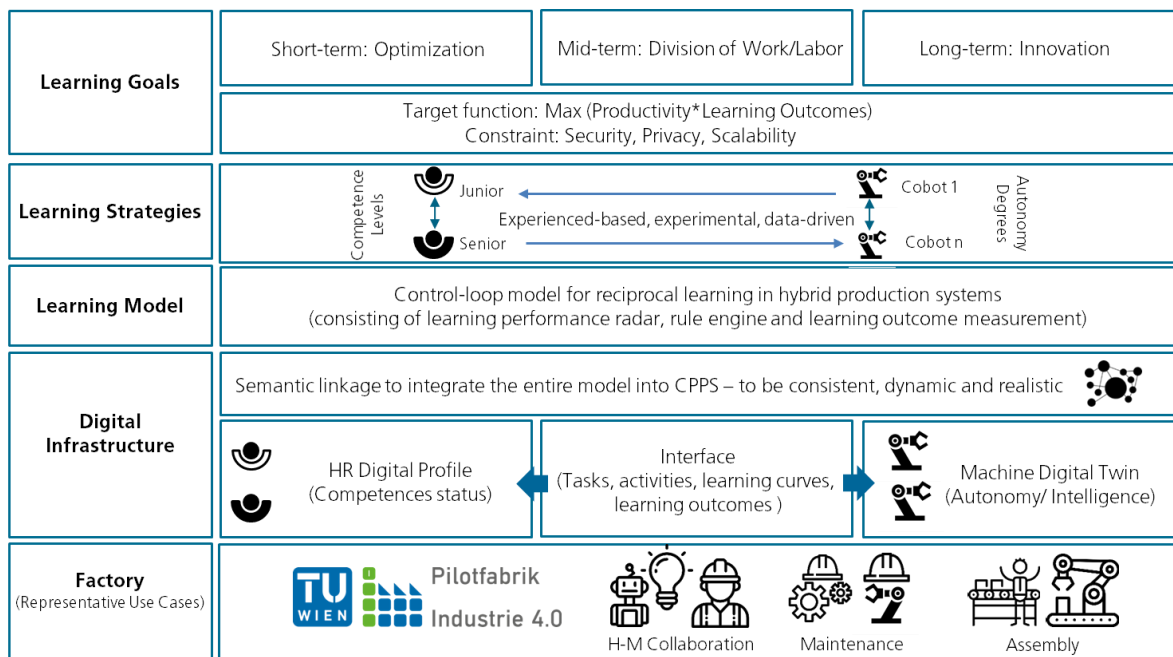


Figure 2. AUTODIDACT – An integrated human-machine collaboration framework for mutual learning

From a design perspective, AUTODIDACT consists of four functional layers, excluding the factory layer, consisting of representative use-cases in manufacturing and assembly units. These layers are introduced in the followings:

- **Digital infrastructure** consists of human workforces and machine’s digital profiles, known as HR Digital Profile and Machine Digital Twin, respectively. In addition, it features taxonomies of tasks, domain ontologies, and associated statistical models and indicators for estimating learning curves and measuring learning outcomes. The entire digital profiles are semantically linked to the existing cyber physical production systems (CPPS) for dynamic acquisition and exchange of knowledge.
- **Learning model** is a control-loop model that assists in building learning profiles and trajectories for each group of learners as well as identifying and measuring the mutual learning outcomes. It includes a learning performance radar and rule engine to facilitate monitoring and assessing the learning outcomes.
- **Learning strategies** refer to experience-based, experimental and data-driven strategies enhanced by machine learning and statistical learning methods for both groups of learners, i.e. human or cobots in various competency and autonomy level, respectively. It mainly deals with various learning strategies to improve not only unidirectional learning ( $Human_i \rightarrow Machine_j$ ,  $Machine_j \rightarrow Human_i$ ,  $Human_i \rightarrow Human_h$ ,  $Machine_j \rightarrow Machine_k$ ) but also bidirectional ( $Human_i \leftrightarrow Human_h$ ,  $Machine_j \leftrightarrow Machine_k$ ,  $Human_i \leftrightarrow Machine_j$ ).

- **Learning goals** feature the target function that should link productivity to learning outcomes under certain constraints and boundary conditions such as security, privacy, scalability, etc.. The outcome is used for progressing towards the factory goals, i.e. i) short-term: optimization of tasks and processes, ii) mid-term: new division of works between human and machine workforce, and iii) long-term: innovation in products and services.

Human-robot collaboration (cf. Figure 3) is one of the typical use-cases in smart factories, which represents certain characteristics of mutual learning, i.e. participation of two groups of learners in performing tasks, including shared tasks, and at the same time the acquisition of (new) knowledge within a dynamic and changeable environment. In this case, the teacher and learner role (i.e. senior and junior) can be identified depending on the human competences and performance determinants (e.g. constitutional, disposition, adaptation, qualification and competence characteristics) as well as the machine’s (robot’s) intelligence and technical functions/conditions represented by the associated digital profiles, respectively (Hold et al., 2016; Ansari et al., 2018b).

Figure 3 schematically represents the human-robot collaboration in an assembly cell, consisting of two human workforces and two cobots. The mutual learning between human workforce (e.g. operator) and cobot occurs by fulfilling the four steps of a so-called questioning, controlling and summarizing, clarification, and prediction, as originally proposed by (Hacker and Tenent, 2002) in the context of reciprocal teaching. The four steps are as follows:

- To check the counterpart with regard to learning success (questioning),
- To change the execution of the activity among them (controlling and summarizing),
- To experimentally transfer the performance of a similar activity to each other (clarification); and
- To allow the other party to make a prediction for the execution of a new task and finally to perform the predicted task execution (prediction)

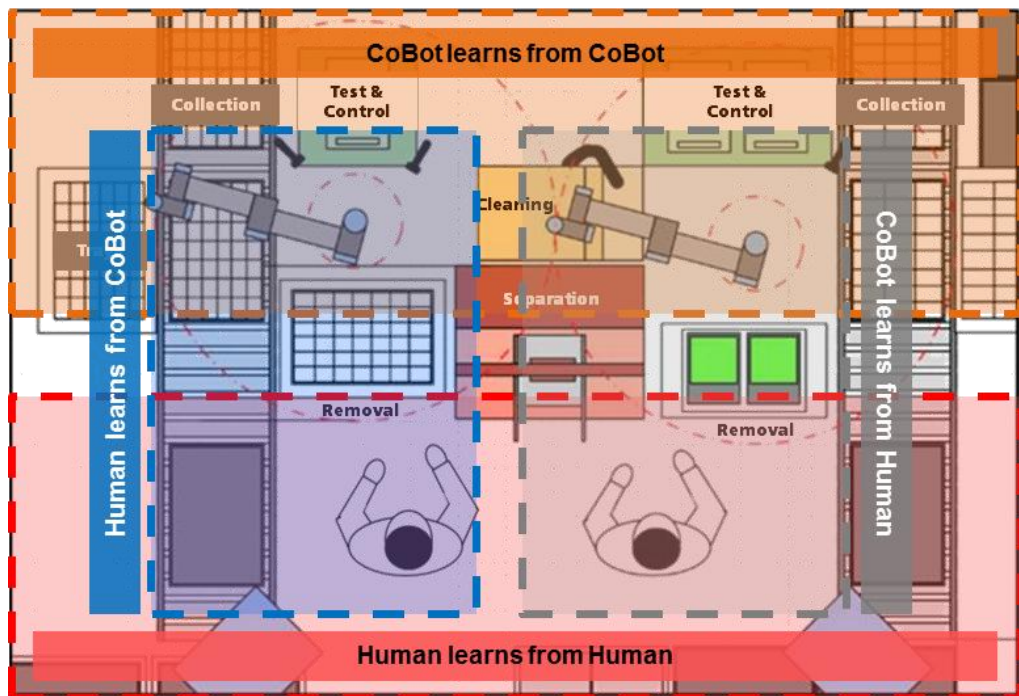


Figure 3. Schematic Representation of Human-Robot Collaboration

For this purpose, the control loop model of mutual learning illustrated in Figure 2 is set into direct interaction with the human workforces and cobots. Based on a fundamental and prospectively planned task distribution between the human workforces and cobots, the success of a corresponding task execution along a learning process is measured (questioning) via different sensor systems. The task execution between human workforces and cobots is changeable and comparable with regard to the learning success (summarizing) via different control logics. Corresponding decisions for a new distribution of activities between them can be

carried out by means of data analysis (clarification). This provides possibilities to dynamically switch between human workforces and cobots in relation to comparable activities (prediction). In this way, new types of learning logic are identified and will be taken into account with regard to an improved distribution of tasks in the forthcoming planning period.

#### 4. FUTURE RESEARCH AGENDA

Naturally, the proposed concept of mutual learning has a dual character affected by human cognitive capabilities and machine's intelligence (i.e. cognitive computing capabilities). Hence, building AUTODIDACT in various smart factories is tied to theoretical and application-oriented research in both human- and machine specific learning domains. In particular, the following steps should be foreseen:

- 1) To define learning profiles and trajectories for both human and machine workforce e.g. in TU Wien's Pilot Factory Industry 4.0, considering specific use-cases in three areas of human-robot collaboration, maintenance and assembly.
- 2) To define AUTODIDACT's system specifications for modeling and measuring mutual learning, including technological and non-technological requirements and constraints.
- 3) To build up AUTODIDACT's ontological knowledge-base, which specifies the shared conceptualization of tasks and associated domain knowledge between human and machine workforce.
- 4) To define AUTODIDACT's control-loop, consisting a rule-engine (set of rules) for inferring optimal task sharing and measuring learning outcomes in relation to key performance indicators (KPIs) used in production management.

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