Diplomarbeit

Numerical Simulation and Analysis of Human Work-based Learning in Smart Factories using Analytic Hierarchy Process

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Wien, im Februar 2021

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Ich habe zur Kenntnis genommen, dass ich zur Drucklegung meiner Arbeit unter der Bezeichnung

Diplomarbeit

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Wien, im Februar 2021

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Kurzfassung

Traditionelle Fabrikationsprozesse verändern sich von einfachen, isolierten Aufgaben zu einer hoch automatisierten Kollaboration multipler Systeme. Durch diese Veränderung erhöht sich der Bedarf an hochqualifizierten Mitarbeiter, welcher nicht durch das derzeitige Arbeitskräftepotential am Arbeitsmarkt gedeckt werden kann. Dadurch wird mehr Bildung von Mitarbeitern benötigt, um den neuen Anforderungen zu entsprechen. Trainings sollten ideal konzipiert werden, um den Bedürfnissen zukünftiger Aufgaben gerecht zu werden. Externe Faktoren wie Arbeitsunterstützungssysteme oder Wissenstransfers von Arbeitskollegen, welche den Lernprozess beeinflussen, sollten kontrollierbar sein und den exakten Lernbedürfnissen entsprechen. Vorherrschende Lernmethoden entsprechen nicht den Bedürfnissen der Nutzer zugeschnittenes Wissen für spezifische Aufgaben zu erlangen. Des Weiteren kann die Vielfalt an Faktoren in cyber-physisch-sozialen Produktionssystemen nicht durch existierende Modelle abgebildet werden. Wissen kann über verschiedene Wege übermittelt werden, wie beispielsweise Lernen am Arbeitsplatz oder im Klassenzimmer, jedoch ist der Output des Trainings schwer kontrollierbar und vorhersagbar. Heutzutage wird der Lernprozess hauptsächlich retrospektiv durch Evaluationsmethoden analysiert, welche nicht an den Arbeitsprozess angepasst sind. In Bezug auf die Vorhersage zur Verbesserung der Arbeitsleistung durch vermehrte Übung, erlaubt bisher nur das Modell der Lernkurve Aussagen zur Durchführungszeit zukünftiger Aufgaben. Dieses Modell berücksichtigt jedoch nicht den Einfluss mehrerer Faktoren. Daher soll ein Modell entwickelt werden, welches erlaubt das Lernergebnis vorherzusagen und Trainings effizient zu planen. Dieses soll auf cyber-physisch-sozialen Produktionssystemen anwendbar sein und die Mensch-Maschine Interaktion mit intelligenten Einheiten modellieren. Dabei sollen verschiedene Szenarien abhängig von der Entscheidungsmacht innerhalb des CPSPS berücksichtigt werden. Um dieses Modell im industriellen Umfeld anwenden zu können, ist eine Verbindung mit Leistungskennzahlen notwendig zur Analyse einzelner Faktoren auf die gesamte Effizienz. In dieser Arbeit wurde ein prädiktives Modell durch die Evaluation existierender Lerntheorien und der Analyse von menschlicher Interaktion in CPSPS entwickelt. Vorhandene Faktoren innerhalb des CPSPS, welche vorhanden waren, wurden klassifiziert und in das entwickelte Modell aufgenommen. Das Modell wurde durch einen analytisch hierarchischen Prozess optimiert. Die Ergebnisse zeigen, dass die Vorhersage verschiedener Einflussfaktoren auf das Lernen möglich war. Für diesen Algorithmus wurden generische Daten verwendet, welche Aussagen in Bezug auf verschiedene Szenarien der Entscheidungsmacht in CPSPS auf den Lernprozess zuließen. Leistungskennzahlen wurden berechnet und erlauben eine Analyse der Einflussfaktoren. Verschiedene Lernszenarien in Bezug auf den Einfluss unterschiedlicher Faktoren können verwendet werden und determinieren

den effizientesten Weg, den gewünschte Lernerfolg zu erreichen. Zukünftige Forschung soll den Einfluss und die Beziehung der Faktoren untereinander bestimmen. Eine Erweiterung des Modells um andere Faktoren wie beispielsweise Umwelteinflüsse könnte in einer höheren Präzision des Modells resultieren. Eine weitere Limitation dieser Arbeit ist die fehlende Validierung des Modells anhand von Daten aus dem Feld, welche bei zukünftigen Studien berücksichtigt werden soll.

Abstract

Traditional fabrication processes are changing from simple isolated tasks to a highly automated collaboration of multiple systems. Due to this change, an increasing need of highly qualified employees emerged which cannot be covered by the current workforce potential on the labour market. This requires further education of present employees to meet the new demands. Trainings should be ideally designed to fit the needs of the workers future tasks. External factors influencing the learning process, such as work support systems or knowledge transfer from working colleagues should be controllable and applicable to meet the exact learning demands. Current learning methods do not meet the user's needs to gain tailored knowledge for specific tasks. Furthermore, the variety of factors present in cyber-physical-social production systems cannot be represented by existing learning models. Knowledge can be transferred via different paths, such as workplace or classroom learning but training output is hardly controllable or predictable. Nowadays the learning process is mainly analysed retrospectively by evaluation methods based on theories not adapted to today's working processes. In terms of predicting performance improvement through advanced practice, only the model of the human learning curve allows to calculate future task execution times but does not allow to take several influencing factors into consideration. Therefore, exists a need to design a tool which enables to predict learning outcome and plan trainings efficiently. Applicable to cyber-physical-social production systems modelling the interaction of humans with smart entities and taking into account the different scenarios depending on the decision authority within the CPSPS. For the application in an industrial environment, the connection towards key performance indicators allows to analyse the impact of influencing factors on the overall efficiency. In this thesis a predictive model was developed by the evaluation of existing learning models and the analysis of the human interaction in CPSPS. Factors available in CPSPS were researched and classified and incorporated in the developed model. The model was optimized by applying an analytical hierarchy process. The results indicate that the prediction of different factors influencing learning was possible. For this model generic data were incorporated in the algorithm and allowed to conclude about the learning process for different scenarios of decision-making authority in CPSPS. A connection towards the key performance indicators was generated allowing to analyse the influences of the used factors. Due to the more efficient usage of factors influencing the learning curve, a better control of the learning process is possible with this approach. Knowledge transfer can be planned in a precise way based on the required demands. Different learning scenarios regarding the impact of factors can be used and evaluated to determine the most efficient way to reach the desired goal. Further research is needed to determine the influence and relationship among the factors. An extension towards further factors such as environmental influences could

result in a higher precision of the model. Another important limitation to this study is the validation of the model by field data which should be considered for future research.

Table of Contents

1 Introduction

The first chapter of this theses gives an introduction to the topic starting with the motivation of this work followed by the problem statement. Objectives of research and the research questions are defined in 1.3 followed by the research methodology and the structure of this thesis.

Figure 1: Structure of the chapter 1

1.1 Motivation

In the light of today's Covid-19 pandemic, we have been able to observe a large amount of companies being forced to deal with digitalization. Most of their workforce had to switch from onsite to remote work from one day to another. In the United States, 62% of employed people had to work from home.[1] This is a good example of how fast external circumstances can change, how fast employees need to adapt and how important learning is in a working environment.

The traditional means of manufacturing are increasingly being transformed into a structure which includes a higher degree of automation and flexible production systems. Emphasis is placed on the interconnectivity of production systems with their environment, which includes planning, management and maintenance systems.[2] To cope with these new challenges, the skillset required by human workers in open socio-technical systems is similarly changing. By upgrading these production systems to cyber-physical-social systems, the tasks carried out by the human workforce are changing from predominantly manual and digital tasks to system supervision and higher-level decision making.[3] A large number of highly qualified personnel is needed, with gaps being expected between the required and available workforce for professions requiring specific qualifications such as the ability to handle complex systems and the skills to interact with smart entities.[4] Manufacturing enterprises face completely new challenges in employee training and learning based on today's tasks and foreseeable tasks of the future.

[1] Cf. Friedman (2020).
[2] Cf. Abele et al. (2006, p. 433).
[3] Cf. Benešová and Tupa (2017, pp. 2196ff.).
[4] Cf. Abele et al. (2019).

In today's working environment, high flexibility and increasing knowledge of systems and processes are required by the workforce.[5] A high diversity of products requires complex systems and processes.[6] The increasing complexity of today's production systems, so-called sociotechnical systems, requires skilled workers who can cope with not only multiple systems of various manufacturers but also complex software solutions and extensive knowledge of the processes. Digitalization offers solutions to administrate and control the multitude of systems and tasks.[7] By moving towards a more digitally supported workplace, the requirements towards the workforce are changing as well. To cope with the current changes, required qualifications include but are not limited to IT knowledge and abilities, data processing, analytics and statistical knowledge.[8] Curricula at schools and universities are changing and adapting slower than the needs of the job market, which results in a gap of the required and available competences of the available workforce[9]. Employers are therefore obliged to organise their own training and educational measures.[10]

1.2 Problem Statement

The interaction with robots in sociotechnical systems defines a new way of skill distribution and skill matching.[11] During the performed task, ideally a mutual learning process is happening between human and the intelligent entities.[12] This process of mutual learning is defined by the distribution of skills for the performed task. Depending on the level of competencies of both human and system, a transfer of knowledge can either occur from human to production system, the other way around or even in a bidirectional way.[13]

Important questions regarding the improvement of these learning processes such as their influencing indicators are still unanswered. Literature suggests multiple methods of measuring learning curves, but only a small number of methods can be used in learning factories.[14] To better understand and evaluate the effects of employee training and the increase in output generated by skilled workers, it is essential to determine the underlying factors and their influences.[15] Especially in an Industry 4.0 environment,

[5] Cf. Industry 4.0 – The employee's role.
[6] Cf. Gaub (2016, p. 401).
[7] Cf. Karre et al. (2017, pp. 207ff.).
[8] Cf. Karre et al. (2017, p. 209).
[9] Cf. Benešová and Tupa (2017, p. 2196).
[10] Cf. Huba and Kozak (2016, pp. 103ff.).
[11] Cf. Ansari, Erol, and Sihn (2018, pp. 117ff.).
[12] Cf. Ansari, Hold, Mayrhofer et al. (2018, p. 64).
[13] Cf. Ansari, Erol, and Sihn (2018, p. 119).
[14] Cf. Glass et al. (2018, pp. 155ff.).
[15] Cf. Lim and Morris (2009, p. 292f.).

workers need to be able to cope with the new challenges and meet the demand in high skills required.[16]

The identified problems can be summarized as followed:

- The existing methods to assess learning are mostly based on the same retroactive approach. We are missing a possibility to determine how changes in the learning and working setup can influence the learning process outcome.
- The influence of single factors on human learning has been researched but no model is available taking into account that the learning process is influenced by a multitude of factors.
- As described above, the learning process in CPSPS differs from typical working environments. Learning curve models that allow to determine the performance improvement after certain number of repetitions do not take into account the distribution of decision-making authorities in CPSPS
- Training and learning have the main purpose to enable a worker to perform its designated task in an accurate way, which results in a higher work performance. Every change in performance is observable by analysing select key figures. So far, no connection has been established from the factors influencing the learning process to the observable performance indicators.

1.3 Objectives of Research and Research Questions

The objectives of this research are triggered by the increasing demand of new solutions for industrial training as well as training evaluation. Evaluation methods for employee training are still based on the same theories as they were decades ago. The first objective would be to develop a framework to analyse learning outcome adapted to the needs of today's production systems. Working in cyber-physical-social production systems requires for the human worker to interact with other workers, machines and smart entities. The role of the human worker differs depending on the setup of his working environment. A second objective would be to evaluate the human learning process for different working conditions, such as the human worker being in charge or the smart entity taking the decisions. In a cyber-physical-social environment, a variety of factors are present and influencing the human learning process. Little is known about how a variation of these factors effects the human learning and how such a change in learning performance can be observed and analysed. A third objective would therefore be to conduct an analysis of the factors influencing human learning and connecting them towards observable indicators to rate the learning effect. Together with these objectives, an overview of the theoretical background shall be provided as well as current relevant applications. Current and further trends of learning in industrial

[16] Cf. Karre et al. (2017, p. 209).

environments shall be identified and even expanded by possible further applications. The rise of new technologies in production systems has changed the working environment in a drastic way with workers' tasks changing.

The objective of creating a connection between the factors influencing human workplace learning and existing key performance indicators is established by answering the two following research questions:

- RQ1: How are external factors influencing the human learning curve in a human-centred cyber-physical-social production system?
- RQ2: How can a human learning model be connected towards existing key performance indicators and how can they be predicted using a numerical simulation method in a realistic use case?

To evaluate the human learning process in a CPSPS for different working conditions, following research question targets the differences between human learning in a human-centred and a system-centred production system.

- RQ3: In a cyber-physical-production system, does the human learning curve differ based on the decision-making authority of the setup? Does a human-centred approach provide a different learning curve compared to a system-centred approach or an equal decision-making approach?

The expected outcome of this research should address the needs shown in the problem statement and offer a solution or a framework that can easily be used and adapted for a multitude of workplace setups. The developed model should be able to include all the present factors influencing the learning process. It should be easily adaptable to changing working and learning conditions. A connection of the improvement of the learner towards existing key performance indicators would enable the evaluation of the factors in place such as the required investments in learning or working support systems in order to achieve a certain improvement of the analysed process.

1.4 Methodology of Research

The methodology used for this research is based on design science as it is well-suited to expand the learning curve model and therefore represent the learning process in an accurate way. As a tool, the design science research process (DSRP) is used to apply design science and create a reliable model to answer the previously defined research questions.

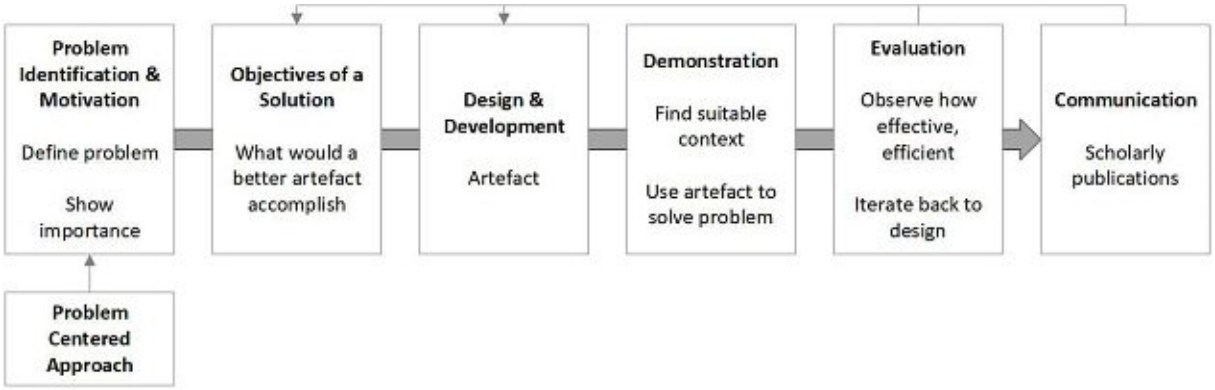

Figure 2: Design science research process (DSRP) model[17]

As shown in Figure 2, the first step consists of identifying the problem and showing the importance of a solution to it. The objectives should be defined to ensure that the solution tackles the right issues and provides the requested answers and insights. The main part of the design science research process is the creation of an artefact that solves the previously defined problem. After this step, the developed model should be evaluated and the feedback should be integrated in the next step of the model evolution. The last step is the communication of the results as well as the developed model.[18]

[17] Peffers et al. (2006, p. 93).
[18] Cf. Peffers et al. (2006, pp. 86ff.).

1.5 Structure

The beginning consists of an exploration of the theoretical background (2) in which human learning (2.1) such as the human learning curve (2.2) and their influencing factors (2.3) are explained. As a next step, a short introduction of machine learning and artificial intelligence (2.4) is given. The technical requirements (2.4.2) and the application in an industrial environment are presented regarding cyber-physical-social production systems and industrial AI. The last part of the theoretical background consists of the learning process in CPSP (2.5) and the decision making in such environments (2.5.1).

The current state of the art in terms of learning assessment methods is discussed in Chapter 3. Both human learning assessment methods (3.1) and machine learning assessment methods (3.2) are discussed and compared. A last step is the definition of the gap (3.4) between available and required methods.

The model development is performed in Chapter 4. After the presentation of the methodology (4.1), the theoretical model is developed in five steps (4.2–4.6).

To validate the model, a simulation in a maintenance use case is performed (5.1). Different approaches that could occur in a CPSPS are discussed (5.2). Last steps are the connection of the model towards measurable KPIs (5.3) and the development of a dashboard (5.4) facilitating the usage of the model.

Chapter 5.5 displays the results for all the approaches developed (5.5.1–5.5.3). A comparison is performed (5.5.4) and the influence of the results on the KPIs is analysed (5.5.5)

As a last step of this thesis in chapter 6, the results are analysed, research questions are answered and possible next steps are defined.

Figure 3 offers a graphical representation of the structure of the thesis including the allocation of the chapters towards their respective pendant in the design science research model.

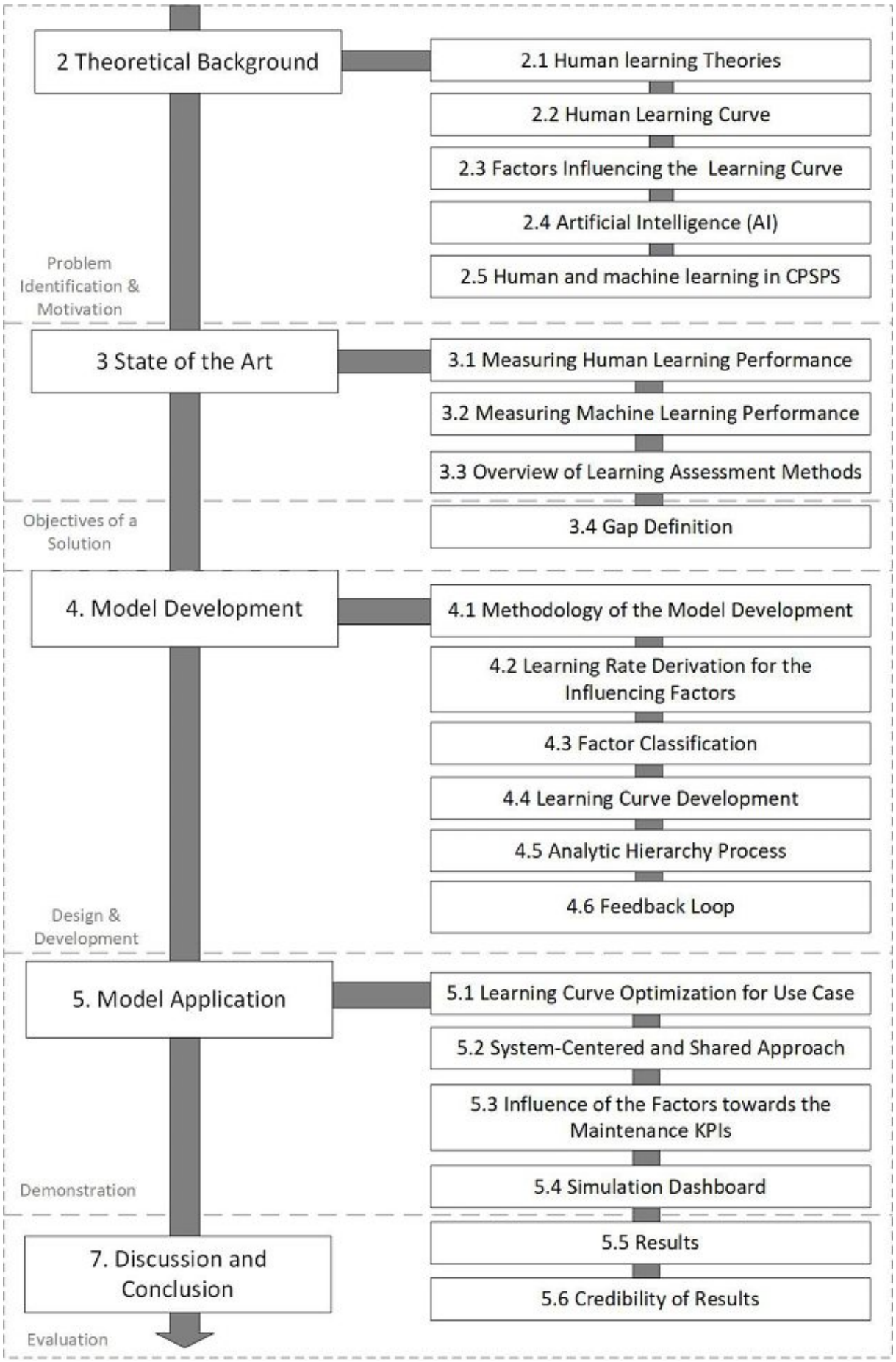

Figure 3: Structure of the thesis

2 Theoretical Background

When analysing the interest in human and machine learning, one can clearly see that in the last ten years, the interest in machine learning was continuously growing. As shown in Figure 4, which represents the amount of Google searches of the terms “machine learning” and “human learning”, the interest in machine learning has exceeded the interest in human learning by far over the last ten years. Even though the interest in human learning is at a constant level, its importance is still at a very high level as the rise of emerging technologies requires specific knowledge that can only be obtained through human learning.

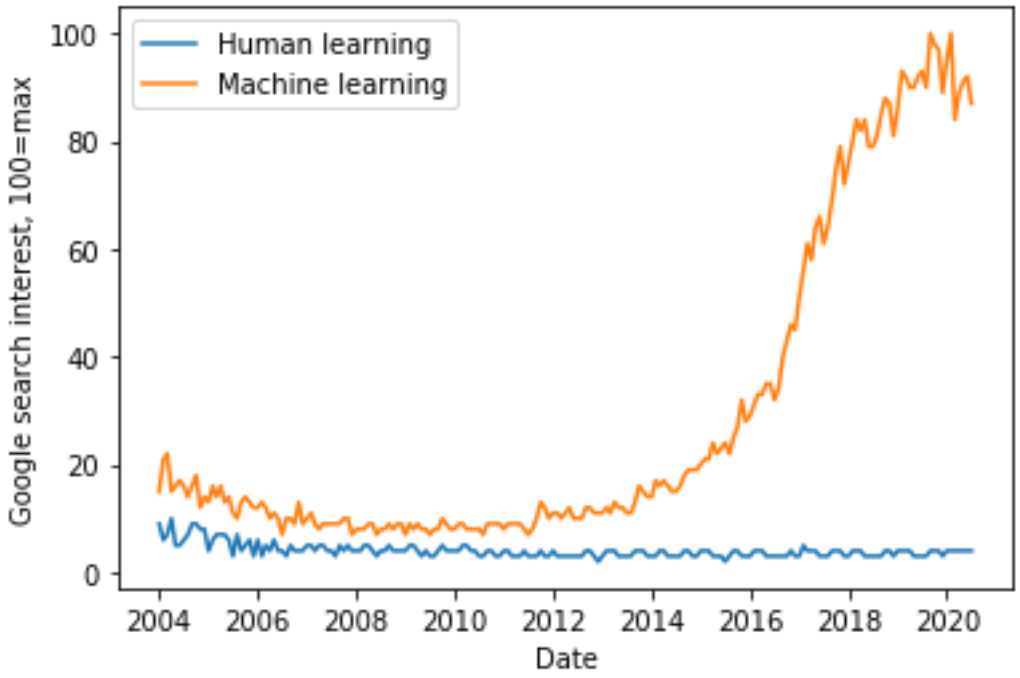

Figure 4: Google search interest for human learning and machine learning[19]

The first step is to understand the learning process which enables the creation of the mentioned competencies and knowledge. To completely analyse the process of learning, it is essential to understand the underlying mechanisms for both humans and machines. Figure 5 shows the structure of this chapter, starting with the theories explaining human learning. Followed by the existing learning curve theories measuring improvement during the learning process and the factors influencing the shape of the learning curve. The theories behind the improvement of the system component is elaborated in 2.4. The last point in this chapter analyses the learning process of humans and machines in cyber-physical-social production systems.

[19] Google Trends.

Figure 5: Structure of Chapter 2

2.1 Human Learning Theories and Transformation to Workplace

A general definition of learning is "the process of getting an understanding of something by studying it or by experience".[20] Learning cannot be observed but only registered through the permanent changes in performance or actions. This makes it difficult to measure learning as performance changes can occur due to different reasons and are influenced by a variety of factors.[21] To ensure that these facts are taken into account, learning can be defined as 'a relatively permanent change in behaviour due to past experience'.[22] Several learning theories have been established and are widely applied in teaching environments. There are multiple options on which level learning can be described. In the following chapters, the neurophysiological as well as the cognitive and behavioural theories will give a broader overview about learning paradigms.

The learning process takes place in the human brain, where changes in the subcortical system are caused by conditioning.[23] Therefore, a deeper understanding of neurophysiology (**Neurophysiology of Learning**) is recommended, specifically the study of the human nerve system. It is responsible for information input and transformation of sight, smells, feelings, noise and tactile sensations and converts this information into chemical and electrical signals.[24] The interaction of neurons in our brain enables us to process those electrical and chemical signals and transforms all the previously named physical sensations and experiences. Neurons are responsible for receiving and sending information from and towards muscles and organs via both electrical and chemical signals. Neurons are human cells with a cell body, thousands of short branches called dendrites which receive the information and an axon which sends the information.[25] About 100 billion of neurons are contained in our brain and spinal cord, connected to one another forming a neural network. The information is passed from one neuron to another by electrochemical reactions at the connection

[20] Cambridge Dictionary.
[21] Cf. Gross (2010, p. 175).
[22] Coon (1983).
[23] Cf. Thompson et al. (1972, p. 76).
[24] Cf. Zimmermann (2018).
[25] Cf. Schunk (2012, p. 32).

points called synapses.[26] From a neuroscientific point of view, learning is the process of forming and strengthening neural networks introduced by Donald Hebb (1949) in his theory about cell assembly.[27] If a person is looking at a specific object, for example, this will be internally represented by the activation of a set of cortical neurons which Hebb called cell assembly. If the endurance of the neurons' activation is long enough, consolidation will occur by strengthened connections between neurons.[28] By stimulation in different ways, the neural connections are strengthened so that they respond to and transform information faster.[29] In this way, learning is in simplified terms the collection of neurons which fire and then wire together[30]

When moving beyond the neurophysiology of learning, many learning issues are still being discussed. Out of these discussions, multiple learning theories have emerged.[31] In the following subchapters, the most important **learning theories** are being discussed.

Starting in the 20th century, **behaviourism** was introduced by John B. Watson who applied the findings of Ivan Pavlov to human behaviour. He experimented with the popular Pavlovian dog where a neutral stimulus (sight of the trainer) was combined with a natural stimulus (food) and this evoked the reaction of salivation. Due to the association, the neutral stimulus alone evoked the reaction which is now known as classical conditioning.[32] In human behaviour, classical conditioning can be used to explain learning as a reaction to environmental events.[33] Using conditioning theories, learning is explained as a response to a stimulus and the creation of an association between stimuli and responses.[34] Operant conditioning implies that environmental factors act as a trigger for responses and reinforcement of the stimulus increases the likelihood of the response for future stimuli.[35] This means that we know which reaction will be successful.[36] Therefore, Skinner distinguishes between four behavioural responses. If a positive stimulus follows upon a behaviour, this behaviour will be reinforced with a high probability. Vice versa, if unpleasant stimuli occur upon shown behaviour, this will be perceived as punishment. As soon as stimuli are removed, the first option will resemble the last mentioned one, when pleasant stimuli are removed, it will be received as punishment. If an unpleasant stimulus upon shown behaviour is removed, this will reinforce the shown behaviour, which is known as negative reinforcement. According to this theory, schoolchildren will study more eagerly if they

[26] Cf. Wolfe (2001).
[27] Cf. Hebb (2002).
[28] Cf. Bear (2015).
[29] Cf. Bransford (2000).
[30] Cf. Bear (2015).
[31] Cf. Schunk (2012, p. 21).
[32] Cf. Berk and Schönpflug (2011, p. 19f.).
[33] Cf. McLeod (2020).
[34] Cf. Watson (1998, pp. 1ff.).
[35] Cf. Schunk (2012, p. 88f.).
[36] Cf. Kiesel and Koch (2012, p. 83f.).

have been praised by their teacher for their good studying.[37] To summarize the aforementioned theories, the factors which influence learning are both the duration and intensity of the stimuli upon observable behaviour. The response to a stimulus therefore is dependent on the reinforcements that were developed in the past. To acquire complex skills, it is necessary for the reinforcement to happen in small steps towards the mastering of the desired skills.[38]

Contrary to the assumptions defined in the previous learning theory, the main idea of **social cognitive theory** is that learning occurs mainly in a social environment and the human cognition.[39] Observation and studies of other people's actions, media or interaction enable humans to learn from their social environment.[40] There are two forms of social learning: on the one hand humans learn through automatic imitation, as for example by imitating the same arm movements as their opposite, which was shown by Rizzolatti's research on mirror neurons.[41] On the other hand, there are also behaviours which can be learned via imitation consciously.[42] This learning mode was defined by Albert Bandura as social cognitive theory. This thesis focuses more on conscious learning which is why automatic imitation learning is left aside.[43] Several key factors have been determined in this theory. The key factors which determine if the behaviour is shown are attention, memory, motor reproductive ability and motivation. Behaviours will be learned with a higher probability if more attention is paid to the learned content. For the reproduction of learned content, memory processes are important as they determine how the content will be represented in the memory. For motor tasks, motor abilities enhance the probability to imitate the learned task. The last factor which determines learning in Bandura's theory is the motivation. Only if learners are more motivated to learn a certain task, it will be stored in memory.[44] Social cognitive theory is very useful for educational purposes. It highlights the importance of learners' self-efficacy and its influence on the learning outcome as they are encouraged to set goals and evaluate their learning outcomes.[45]

Information processing theory cannot be classified as a proper learning theory as it is more a collection of theories on how to sequentially process and transform information.[46] In a psychological framework, the term 'information processing' is rather used as a metaphorical term as the transformation process of information.[47] Information processing is strongly influenced by neuroscience, computer technology

[37] Cf. Bodenmann and Schaer (2006, p. 12).
[38] Cf. Schunk (2012, p. 114f.).
[39] Cf. Berk and Schönpflug (2011, p. 20).
[40] Cf. LaMorte (2019).
[41] Cf. Fabbri-Destro and Rizzolatti (2008, p. 171f.).
[42] Cf. Kiesel and Koch (2012, p. 14).
[43] Cf. Bandura (1979).
[44] Cf. Zimmerman and Schunk (2003, pp. 431ff.).
[45] Cf. Schunk (2012, p. 161).
[46] Cf. Berk and Schönpflug (2011, p. 23).
[47] Cf. Ansorge and Leder (2011, p. 34f.).

and communication technology.[48] A learning process can be seen as the input, transformation and output of information. Information processing theory connects human to computers, as they both perform cognitive processes like learning, decision making or remembering. Learning for example is seen as the processing of information, reading the input, transforming the information or applying different operations and delivering a result as output.[49] An important factor of the information processing system is memory, which is divided into short-term and long-term memory although there also exist theories about the composition of the memory storage claiming that only one memory exists with multiple levels.[50] During the learning process, information is received by the processing system from the sensors, compared to information saved in the long-term memory and stored in the short-term memory, also described as working memory.[51] The information to be processed is divided into propositions, the smallest pieces of information that can be judged true or false, which later form a network.[52] These new propositions are then connected with propositions from the long-term memory which are activated through the new ones. New propositions may be created during this process and stored together with the new and old proposition networks in the long-term memory. The transfer of the information towards the long-term memory represents our definition of learning.[53]

Constructivism emphasizes how knowledge is built resulting out of action and interaction with our environment.[54] It suggests that meaning and knowledge are built out of experiences, which means that everyone constructs their own knowledge internally.[55] The learning process is initiated through external influences that bring the internal state out of balance. As we have an internal force towards an optimal adaptation, cognitive development enables us to reach this state of equilibration[56] Constructivism empowers learners to truly understand what they are learning as well as its backgrounds. The goal is to apply their existing knowledge and experience on real-world problems and create conclusions from their evaluation.[57] The main factor influencing the learning outcome is the learning environment as interaction with their environment enables humans to construct understandings.[58] This implies that guidance towards the relevant themes is more important than providing the right answers. So, learning in general is making up one's own knowledge and not just

[48] Cf. Xiong and Proctor (2018, pp. 4ff.).
[49] Cf. Mayer (1996).
[50] Cf. Cowan (2008, p. 2).
[51] Cf. Gruber (2011, p. 13).
[52] Cf. Schunk (2012, p. 183f.).
[53] Cf. Schunk (2012, pp. 191ff.).
[54] Cf. Packer and Goicoechea (2000, p. 227).
[55] Cf. Shapiro (2002, p. 349).
[56] Cf. Duncan (1995, p. 461).
[57] Cf. Bada and Olusegun (2015, pp. 66ff.).
[58] Cf. Elliott (2000, p. 256).

acquiring it.[59] The learning process is challenging one's own thoughts and schemata and achieving knowledge through that.[60]

Workplace learning used to be the main source of learning in ancient times. Starting with industrialization, the interest in learning rose as job requirements became more important and were harder to achieve solely through workplace learning.[61] In the 1980s with the occurrence of new information technologies and new work concepts, workplace learning occurred more often. This was also due to the gap between the actual learning and the working processes.[62] To adapt towards newer technologies and manufacturing processes, learning factories have been established to cope with the arising challenges in the industry. Learning factories simulate a proper working environment and can therefore be seen as an application of workplace learning.[63]

Knowledge can be obtained through either formal or informal learning at the workplace. Formal learning is happening in workshops or training activities involving a trainer or training material. Whereas informal learning, which is predominant in workplace learning, happens during usual day-to-day tasks, it can be experience-based in the form of changing tasks and increasing autonomy. The occurrence of informal learning is unintentionally, it happens spontaneous and is not planned.[64]

Workplace learning is an application of the constructivist learning theory as people are learning in their workplace through interaction with their environment. They perform a certain task and get feedback about their action which helps them understand and improve. According to Dehnbostel et al. (2001), there can be several models as a source for learning processes. Five forms of work-related learning will be explained in the following.

- Learning by work execution in the real working process: the workplace is also the learning place so that employees are learning from each other by observing and imitating others. Other ways of learning are by communicating, cooperating and helping each other.[65]
- Learning by systematic instruction at the working place: addition of informal learning through the instruction of experienced employees or superiors.
- Learning through integration of informal and formal learning: systematic connection of measures of work-related learning with experience learning in the work process, especially through the high potential of digital media.

[59] Cf. Shapiro (2002, p. 349).
[60] Cf. Brooks and Brooks.
[61] Cf. Billett (2008, 7).
[62] Cf. Arnold et al. (2020, p. 3f.).
[63] Cf. Abele et al. (2019, pp. 63ff.).
[64] Cf. Cacciattolo (2015, pp. 243ff.).
[65] Cf. Dehnbostel (2001, p. 477f.).

- Work-oriented learning: focus of further training measures on the process of the work itself, learning possibilities close to the workplace, digital simulation of work processes.[66]
- Cooperative learning: a form of learning that consists of a group of learners working together to complete a common assignment. The advantages and positive effects of cooperative learning consist of social interaction as well as the task processing of an entire group.[67] Furthermore, the learner can benefit from others' skills and knowledge, which helps in progressing faster and more efficiently.

2.2 Learning Curve

The developed model is based on the learning curve, which is explained in the following subchapters, as it offers the perfect tool to connect learning to output. This is started by exploring the above-mentioned theories explaining the learning curve and continued by an overview of existing learning curves before a new model is developed.

2.2.1 Learning Curve Theories

Several theories explaining the learning curve exist and will be discussed to provide a comprehensive overview of how the learning curve can be explained.

According to Crossmann (1959), the acquisition of skills is the result of making the right decisions and neglecting the wrong ones. This trial-and-error process in which the trainee tries multiple possibilities and stays with the most successful happens randomly.[68] Later, Roberts managed to prove that this trial-and-error process does not consider all possible combinations but only a small search space because all the improbable combinations are known to be worse and therefore have been ruled out in advance.[69] Learning can either be induced or autonomous. Autonomous learning represents learning by doing or first-order learning, which represents working with the process itself and finding a better way to solve a certain task. This happens mostly in well-understood processes that run very stable. Induced learning, on the other hand, is a second-order learning that is triggered by changes of processes, employee training or product changes. Second-order learning happens for example when the company must react to competition and is therefore rather management-induced.[70]

[66] Cf. Dehnbostel (2001, p. 477f.).
[67] Cf. Siegel (2005, pp. 339ff.).
[68] Cf. Crossmann (1959).
[69] Cf. Roberts (1983, pp. 71ff.).
[70] Cf. Adler and Clark (1991).

2.2.2 Log-Linear Learning Curve Model

Learning curves reflect the idea of learning in a production process as they display the performance with increasing learning effort. The first one to introduce the learning curve in 1963 was Theodor Paul Wright, who discussed the decreasing average cost per unit with increasing production level for airplane production.[71] His log-linear model is very often mentioned as the 'conventional learning curve' model.

$$C(x) = C_1 * x^b \text{ , with } b = \frac{\log LR}{\log 2}$$

Formula 1: Average cost per unit

Mathematically, the average costs per unit are expressed by Formula 1, where C_1 expresses the costs of the first produced unit, x is the cumulative production count and b the slope of the learning rate.[72] The learning rate LR can be derived from the progress ratio.

$$LR = 1 - PR$$

Formula 2: Learning rate

Here, LR represents the learning rate and PR the progress ratio, which is the relative amount of cost reduction when doubling the cumulative output.[73]

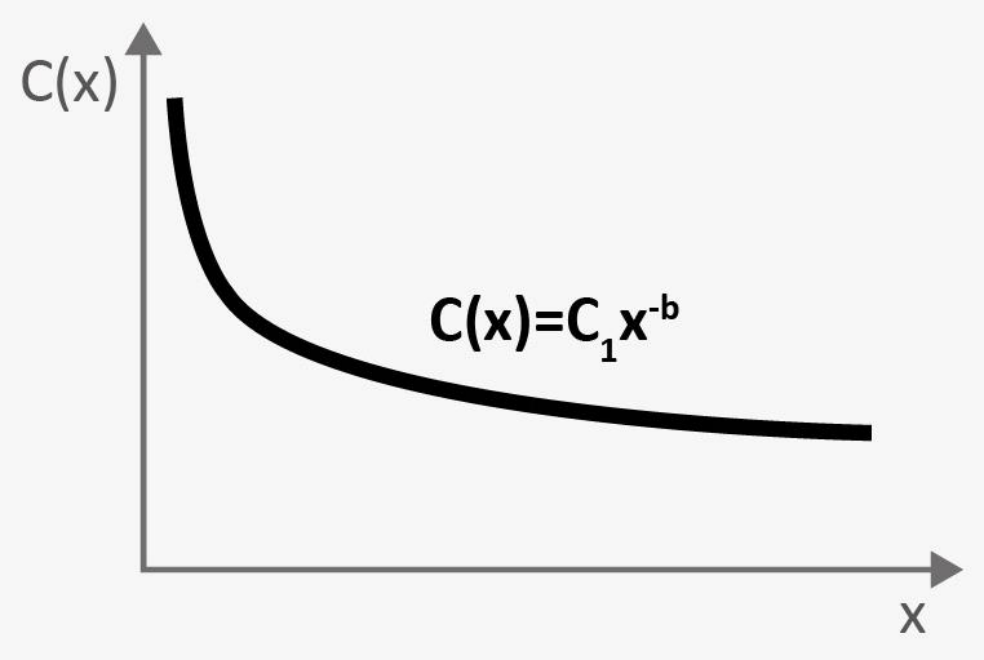

Figure 6: Log-linear learning curve model[74]

[71] Cf. Glock et al. (2019).
[72] Cf. Wiersma (2007, p. 1904).
[73] Cf. van Sark (2008, p. 406).
[74] Jaber (2011, p. 353).

2.2.3 Multivariate Learning Curve Model

The log-linear learning curve model is dependent on a single input factor, the production level. The learning rate is dependent on other factors such as skill level, level of experience availability of training and others. To take these factors into account, the multivariate learning curve model was introduced by Conway and Schultz in 1959.

$$C_x = K \prod_{i=1}^{n} C_i x_i^{b_i}$$

Formula 3: Multivariate learning curve model

In Formula 3, K represents the model parameter which represents the cost of the first unit, C_i is the coefficient of the i-th factor and b_i the learning exponent for the i-th factor.

Multivariate learning curve models offer the possibility to include a multitude of factors and therefore take more reliable decisions when analysing the learning curve compared to the log-linear curve.[75]

2.2.4 Forgetting Curve Model

After a certain time, all knowledge and skills have been forgotten by the human mind. Therefore, it is necessary to consider the forgetting factor when establishing the learning curve. Jaber and Bonney (1996) introduced the forgetting curve to model the increase in time needed to produce another unit due to forgetting after a certain time without learning activity.

$$T(x) = T_1 * x^f, with\ f = \frac{b(1-b) * \log q}{\log (C+1)}$$

Formula 4: Forgetting Curve

In Formula 4, f represents the forgetting factor similar to the learning factor in the learning curve. Contrary to the learning curve, the forgetting curve is not a function of x, the cumulative output, but of q, the amount produced since the end of the last learning period. $C = \frac{t_B}{t_P}$ is the ratio of the brake time t_B, which would result in total forgetting, to the production time of a lot preceding a break t_P. To compute the cumulative output that would have been produced if no break had occurred, Formula 5 is used.

[75] Cf. Jaber (2011, pp. 353ff.).

$$(q+s) = \left[\frac{1-b}{T_1} t_B + q^{1-b}\right]^{\frac{1}{1-b}}$$

Formula 5: Total amount of output without interruption

The number of units remembered at the beginning of a new lot is determined by Formula 6.

$$\alpha = q^{\frac{(b+f)}{b}} * (q+s)^{\frac{-f}{b}}$$

Formula 6: Units of experience at the beginning of a production after an interruption

This is then used to calculate the time necessary to produce the first unit of the following lot by using Formula 7.

$$\tilde{T}_{q+1} = T_1 \left[q^{\frac{(b+f)}{b}} (q+s)^{\frac{-f}{b}} + 1\right]^{-b}$$

Formula 7: Production time of the first unit after an interruption

The production time of the first unit of every lot is then used as initial value for the log-learning curve expressed in Formula 2 until the next break and therefore forgetting occurs.[76]

2.3 Factors Influencing the Learning Curve

After the first introduction by Wright in 1963, lots of studies were published that focused mainly on the proxies for experience. Only some studies focused on the factors that influence the learning curve. To achieve a realistic model, researched influencing factors need to be included in the development. The presented factors include a short introduction and a description of the used research setup.

Economies of scale define the ability to produce at lower costs when producing on a larger scale. **Economies of learning**, on the other side, describe the effect of producing at lower costs due to an increase in experience.[77] The economies of learning have a significant influence on the learning curve as shown in Figure 7. It considers the efficiency of the job as well as the organization design which affect the firm's production rate x where x_0 represents the optimal equilibrium and x_1 represents a lower production rate. This affects first the cognitive learning, which represents a higher problem-solving ability, because the cognitive and motivational abilities of the employee are not optimally used. Furthermore, the manual learning that results from repeating a task and performing it more efficiently each time is affected due to lower

[76] Cf. Jaber and Bonney (1996, pp. 162ff.).
[77] Cf. Besanko (2007, p. 81f.).

repetitions when producing under equilibrium. Both the manual learning effect (a) and the cognitive learning effect (b) are shown graphically in Figure 7.[78]

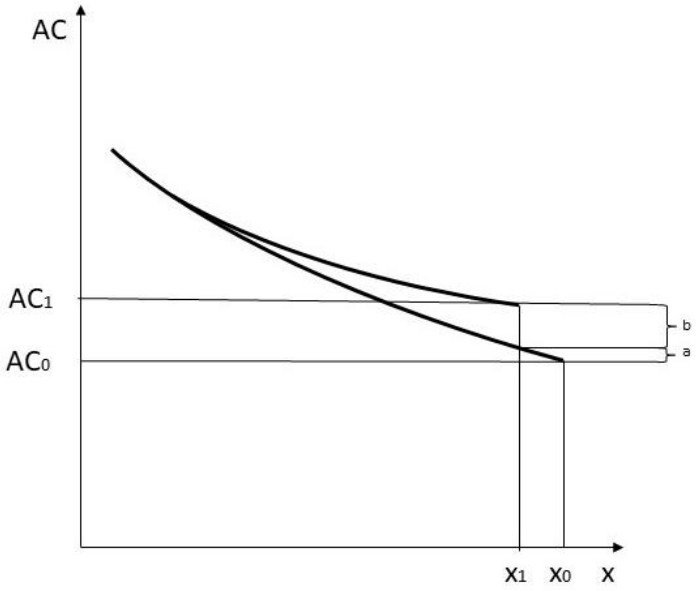

Figure 7: Economies of learning by doing[79]

When talking about type **production technologies**, a well-known example is the production of Ford's model T, the first car manufactured using a moving assembly line. The manufacturing principles developed by Henry Ford were later adapted by other industries. The rise of new production technologies introduced new types of jobs.[80] Learning curves vary with regard to the analysed job. Assembling jobs have a steeper learning curve than manufacturing jobs due to the large amount of direct labour and therefore more learning opportunities. In the example of a machine operator, several parts are built into different products and machine operators have existing experience of specific parts. This could lead to inconsistency in the learning curve of a machine operator as the amount of new and known parts needs to be considered. A skilled machine operator will have a low learning potential as most of the parts that are machined and the manufacturing processes are alike. In conclusion, it is possible to say that direct labour has less opportunities to learn than indirect labour.[81]

Task variety refers to the number of unique tasks being performed on the job. Work that needs non-repetitive activities to be performed is likely to be more interesting and enjoyable.[82] A greater task variety enables the learner to develop a deeper cognitive structure and allows them to link diverse problem domains. The result is a bigger domain of possible actions and methods. The learner can now choose from this pool

[78] Cf. Windsperger (1992).
[79] Cf. Windsperger (1992).
[80] Cf. Tomac et al. (2019, pp. 33ff.).
[81] Cf. Hirsch (1956).
[82] Cf. Morgeson and Humphrey (2006, p. 1323).

of methods and actions to define a solution for a certain problem that may be suitable for other problems as well. Therefore, groups that work on related problems have a significant higher learning rate than groups working on unrelated problems or performing specialized tasks.[83]

Team composition represents the configuration of a team by its team members. A requirement for good teamwork is the required knowledge and skills as well as social traits.[84] Learners who have experience in working in teams have a steeper learning curve when working together in teams than people without previous team experience. Furthermore, working in a group enables better learning performance due to shared knowledge being developed during the work process. In an organizational unit, on the other hand, a greater shared experience amongst the learners does not result in an improved learning and therefore output.[85]

In the Cambridge Dictionary, work **experience** is defined as "the jobs that someone has had, or the type of work they have done, in the past".[86] Prior experience in related domains provides benefits for the development of a steeper learning curve for individual learning. In group learning, diverse experience has a greater impact on learning than specific experience of a domain.[87]

To cope with global competition and pressure on producing at a low cost, manufacturing firms have invested in **process and information technologies** to become more efficient and streamline their processes.[88] The implementation of information technology systems as support results in performance improvement along a learning curve. The introduction of an enterprise resource planning system helps in coordination and delivering information to workers.[89]

Cognitive tasks are tasks that require a person to process new information. This information needs to be processed, saved and re-used at a later time.[90] Manual tasks require motor skills and are physical tasks that require the use of the own body. The **ratio of the cognitive and manual tasks** has been implemented in various models of the learning curve as a cognitive task is remembered after less repetitions than a manual component which needs a large amount of repetition to be initialized completely by the learner.[91]

[83] Cf. Schilling et al. (2003, pp. 41ff.).
[84] Cf. Bell and Vazquez (2019).
[85] Cf. Fong Boh et al. (2007, p. 1328f.).
[86] Cambridge Dictionary.
[87] Cf. Fong Boh et al. (2007, p. 1327).
[88] Cf. Bardhan et al. (2006, pp. 13ff.).
[89] Cf. McAfee (2002, p. 50f.).
[90] Cf. Kester and Kirschner (2012).
[91] Cf. Jaber and Glock (2013, p. 867).

A learn-forget model has been introduced in 2.2.4 to evaluate the occurrence of forgetting when not repeating a task. As lot size is an indicator for the break time between working, **forgetting** can be treated as a consequence of the selected **lot size**.[92] Lot size has been discussed regularly in terms of production optimization. The main problem to be solved is determining the right lot size in a certain period of time to satisfy demand and keep costs at a minimum.[93] Another approach is to evaluate the effects of lot size on the learning effect of employees. Producing in smaller lot sizes reduces the risk of forgetting and therefore minimalizes the time necessary to re-learn. This can be explained by the fact that a certain amount of work divided into smaller lots reduces the length of the production breaks. Forgetting is happening mainly during the break time.[94]

A more detailed explanation of **work and learning assistance** systems is given in 2.4.2. Work and learning assistance systems and their interface to the worker augment the worker's field of view and knowledge base. Examples of interfaces are augmented reality devices that enable alternative ways to train employees compared to traditional training. They offer better training conditions that can lead to a more effective learning curve compared to traditional learning.[95]

2.4 Artificial Intelligence (AI)

AI was first introduced in the 1950s when people began considering the concept of thinking machines, which was triggered by the pioneers in this field like Alan Turing. Two directions were established between 1950 and 1980: strong and weak AI. Strong AI is an AI that could perform any intellectual task of a human being whereas weak AI represents the application of AI techniques.[96] Around 1980, machine learning was introduced with the purpose of enabling the learning of computers and the building of models to produce forecasts. The rise of affordable computing power and the advances in the research of machine learning and AI led to multi-layer neural networks, the basis of deep learning. Deep learning permits us to solve complex problems and is a major tool of cognitive computing, the simulation of human cognitive processes.[97] Figure 8 displays the timeline of AI with the rising focus on machine learning and cognitive computing.

[92] Cf. Jaber and Bonney (2003, p. 110).
[93] Cf. Diaby (1995, p. 533).
[94] Cf. Jaber and Bonney (2003, p. 109).
[95] Cf. Longo et al. (2017, p. 154f.).
[96] Cf. Bringsjord and Govindarajulu (2020).
[97] Cf. Jones (2017).

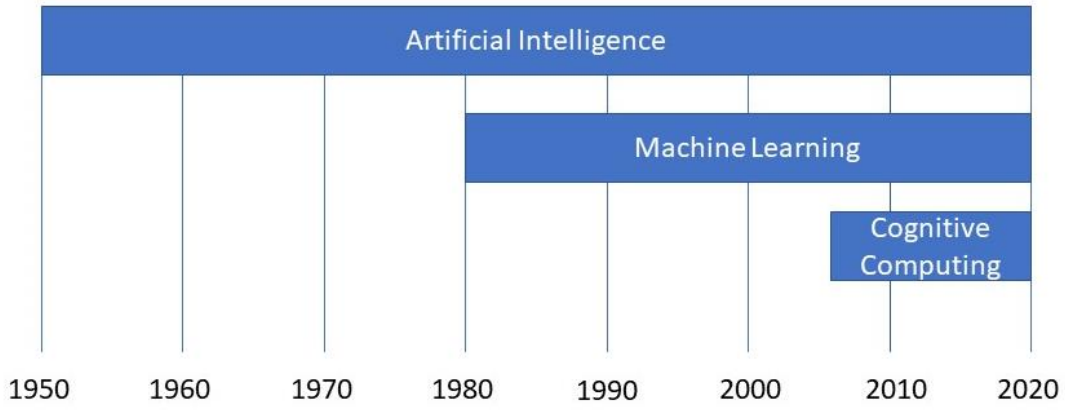

Figure 8: Timeline of modern artificial intelligence[98]

According to Russell and Norvig (2016), four approaches define how a system must react and act to be considered intelligent or being classified as artificial intelligence. They are:

- Acting humanly: To act as a human, the system must be able to communicate, store the received information, use the stored information and process it to answer questions. Furthermore, the system must be able to react to changes of its environment.
- Thinking humanly: To think as a human, the human mind needs to be replicated in terms of being able to replicate the same output when given the same input as a human being. This approach combines psychology and computer models to replicate human thinking.
- Acting rationally: For a system being able to act rationally, it must act in a way to always achieve the best expected outcome.
- Thinking rationally: To think rationally, it is necessary to apply logic reasoning which consists of taking into account the relations between the studied objects.[99]

Artificial Intelligence studies intelligent agents that interact with their environment through sensors and actuators. The way they interact is determined by their environment and the agent type. The following agent types can be identified:

- **Simple reflex agent:** The simple reflex agent is the most basic version of an agent. It only considers the current situation of its environment and does not consider any previous events.[100]

[98] Cf. Jones (2017).
[99] Cf. Russell and Norvig (2016, pp. 1ff.).
[100] Cf. Russell and Norvig (2016, p. 48).

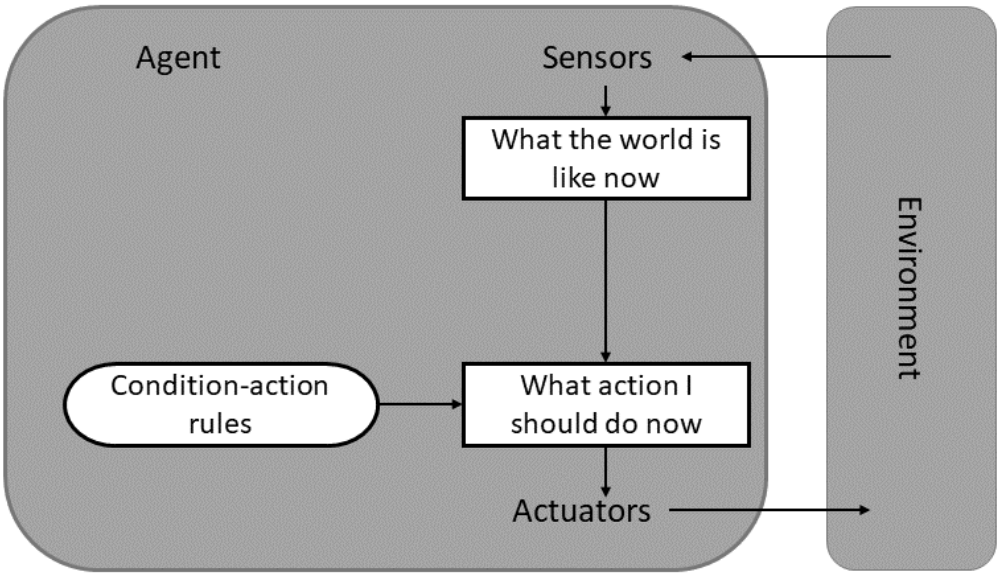

Figure 9: Simple reflex agent[101]

- **Model-based reflex agent:** Contrary to the simple reflex agent, the model-based reflex agent takes previous states into account which are stored by the agent as internal state and being updated after decision taking.[102]

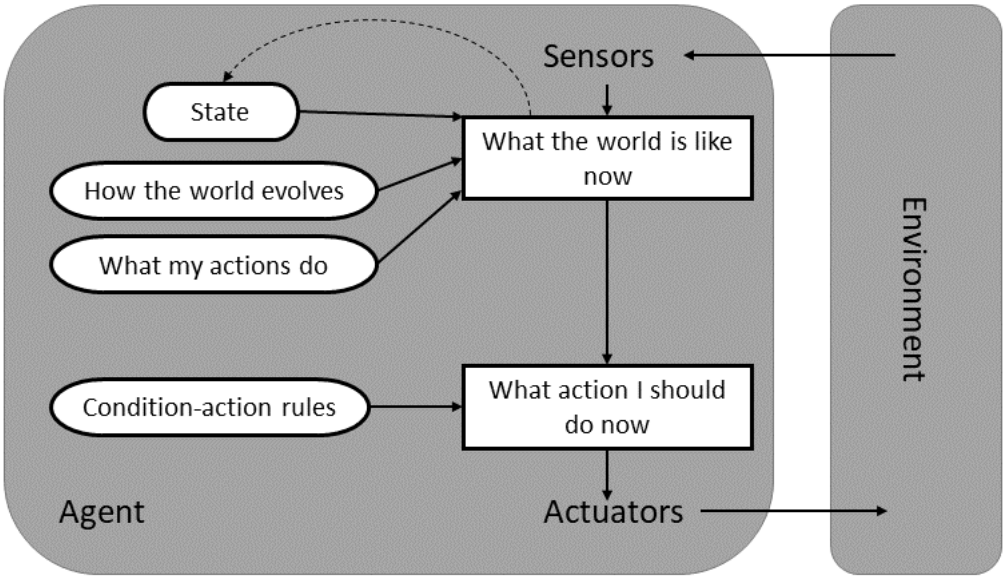

Figure 10: Model-based reflex agent[103]

- **Goal-based agent:** The goal-based agent combines a model-based agent and a desirable outcome of the decision. It is more flexible than a model-based agent because it does not need to add more condition rules if external conditions change.[104]

[101] Russell and Norvig (2016, p. 49).
[102] Cf. Russell and Norvig (2016, p. 50f.).
[103] Russell and Norvig (2016, p. 51).
[104] Cf. Russell and Norvig (2016, p. 52f.).

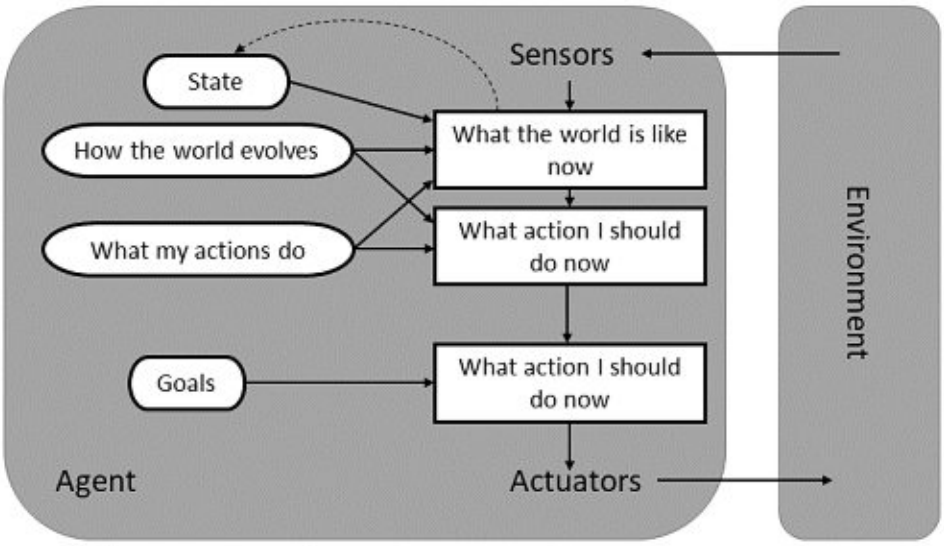

Figure 11: Goal-based agent[105]

- **Utility-based agent:** Sometimes, goals are not sufficient to generate decisions of a good quality as there are many ways to achieve the desired goal with some of these ways being very inefficient. To eliminate inefficient or undesired decisions, a utility function is introduced which maps every state to a number indicating the performance of every state.[106]

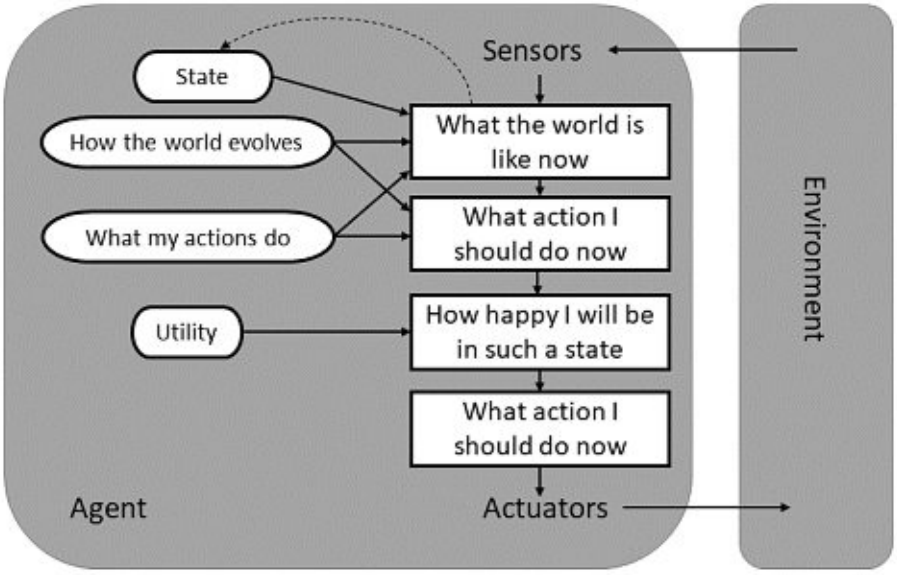

Figure 12: Utility-based agent[107]

- **Learning agent:** To cover all possible environmental conditions, a huge amount of programming would be necessary. To avoid that amount of work, a learning agent was introduced. It starts with no knowledge at the beginning and gets better by learning from its environment. State-of-the-art systems are mainly built

[105] Russell and Norvig (2016, p. 52).
[106] Cf. Russell and Norvig (2016, p. 53f.).
[107] Russell and Norvig (2016, p. 54).

out of learning systems. They consist out of a learning element that enables learning from the environment and the critic providing feedback to the learning element on how the agent is doing. Based on the feedback, the performance element adjusts the actions that are taken. To avoid the performance element from always taking the best decision and therefore not being able to explore other options that may be less optimal in the beginning but better in a long term, the learning agent has a problem generator which suggests actions that lead to new experiences.[108]

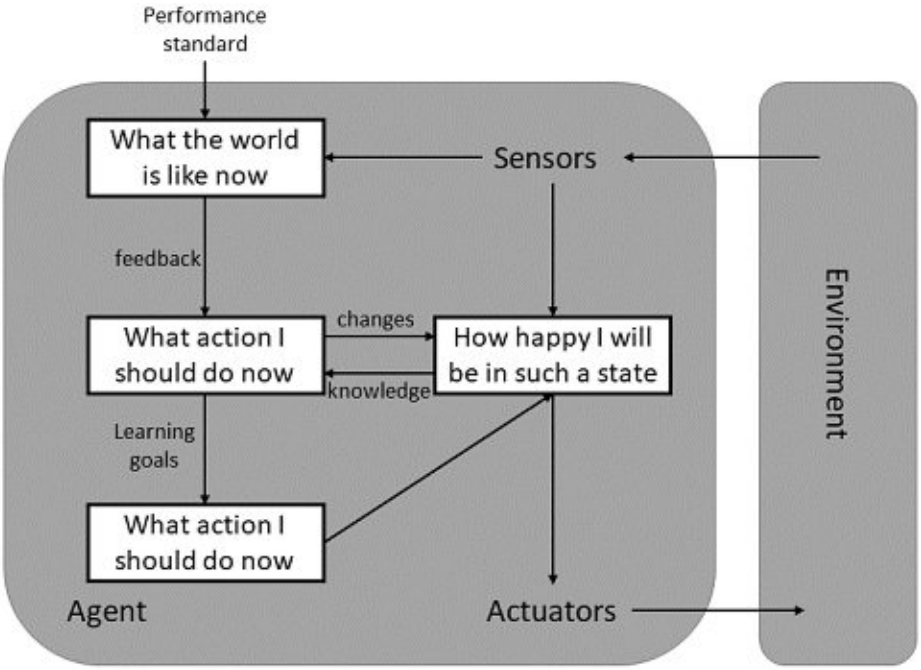

Figure 13: Learning agent[109]

2.4.1 Machine Learning

For an AI application to be able to learn, it requires multiple machine learning algorithms that can process the collected data and provide feedback to the system. The following subchapters represent a short introduction into the most common machine learning algorithms.

Perceptrons are two-layer neural networks used as binary classifiers to classify data into two parts.[110] The input variables are multiplied with a weighting function. The sum of the products is finally activated by a step function with a defined threshold. The perceptron can be seen as a mathematical function that maps a feature vector to a function value and is able to learn by adjusting the weights of the weighting vector

[108] Cf. Russell and Norvig (2016, pp. 54ff.).
[109] Russell and Norvig (2016, p. 55).
[110] Cf. Tyagi (2020).

accordingly. Graphically, it represents a hyperplane that separates the sets of values that are linearly separable.[111]

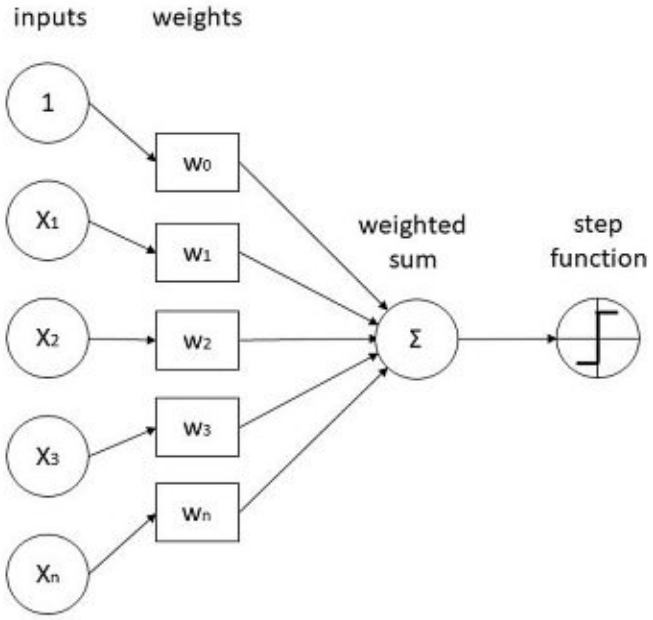

Figure 14: Schematic figure of a perceptron[112]

Contrary to the perceptron's supervised learning approach, **clustering** is an **unsupervised approach** to classify a set of samples into predefined clusters based on one or more attributes of their data. Well-known methods are for example the k-means or nearest neighbour methods.[113]

With k-means, the number of clusters must be known in advance. The cluster midpoints are initialized and selected manually. The data is then classified by its distance towards the nearest midpoint. The midpoints are recalculated until no more changes occur.[114]

Rules-based systems use if-then rules to take decisions based on the delivered input. They represent an easy approach to build expert systems as the rules can be derived from experience and the handling of special situations can be done with special-purpose rules. The graphical representation can portray using a decision tree which offers the advantage of a good overview of the applied rules as well as the designated output. An addition to a typical rules-based system can be a certainty factor or a Bayesian approach to take care of uncertainties.[115]

[111] Cf. Ertel (2017, pp. 183ff.).
[112] Cf. Müller (2017).
[113] Cf. Lei (2017, p. 175).
[114] Cf. Ertel (2017, p. 226f.).
[115] Cf. Shang (2005, pp. 367ff.).

2.4.2 Technical Requirements

The usage of artificial intelligence and its machine learning applications requires a certain environment which includes its place of deployment such as CPPS or smart factories with the necessary hardware and access to digital resources.

The **Internet of Things (IoT)** can be defined as:

"An open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment"[116].

IoT can be understood as a world where physical objects can be represented as virtual data and all objects can interact with each other at the same space and time.[117] The fundamental characteristics of the IoT are its interconnectivity as everything can be connected to the global communication infrastructure, the heterogeneity as hardware can connect through various networks, its dynamic changes in device status and its enormous scale as the amount of devices that communicate with each other will be much higher than the amount of devices connected to the internet.[118]

With human workers being the most flexible asset, their tasks vary accordingly. As support to cope with increasing workload and complexity, intelligent assistance systems were introduced.[119] Trotha et al. (2018) define assistance systems as an interactive interface which encapsulates complexity, increases the acting capability of the user and therefore allows a better usage of the plant. The improved usage can target objectives such as controllability, product quality, efficiency, productivity, comfort or the like.[120] The presented definition does not include an exact description of an assistance system, which is valid for its applications as well. The applications of **work and learning assistance systems** exist in a great variety. Attempts of classification have been made by Trotha et al. (2018) with the following identified categories:

- Level of automation/autonomy
- Decision making tasks
- Context of the assistance system
- Initiative
- Adaptability of the assistance system
- User interaction

[116] Madakam et al. (2015, p. 165).
[117] Cf. Kosmatos et al. (2011, p. 5).
[118] Cf. International Telecommunication Union (2012, pp. 1ff.).
[119] Cf. Gorecky et al. (2014, p. 289).
[120] Cf. Trotha et al. (2018, p. 3232).

- Technology/knowledge base of the assistance system[121]

The application of assistance systems in cyber-physical systems requires a large amount of information and data. Therefore, the cyber level acts as a data hub with all the production and machine data gathered. It allows simulations and the creation of digital twins.[122] The physical context is closely connected to the cyber twin. The operator represents the link between digital and real world assets and is an important link in the closed loop chain which represents an important feedback system.[123] Information is delivered to the user and feedback being provided from the user to the system. For the system, a distinction between low-level and high-level learning is made. Low-level learning acts on the level of a single asset whereas high-level learning considers input from the whole system with all the assets such as multiple production machines.[124]

The connection between the human component and the cyber part is the so-called human-machine interface. The human-machine interface exists in forms such as virtual reality devices that present real-time data to the operator in a virtual environment allowing more efficient training opportunities.[125] Other examples of interfaces are motion recognition that registers physical movement of the user and transforms it into commands or tangible user interfaces that use projection, depth sensors and motion detection to overlay virtual reality information onto physical objects.[126]

Cyber-physical-social production systems (CPSPS) are the industrial application of cyber-physical-social systems (CPSS) which represents the interaction between physical, cyber and social space. CPSS integrate social characteristics whilst using the characteristics of cyber-physical systems (CPS).[127] The structures used in CPPS are very dynamic as there are too many resources that change their composition all the time to perform a fixed planning of the mentioned resources.[128]

The physical space consists of the machines and the equipment, i.e. all the physical devices. The cyber space consists of the information that is gathered, processed and stored. The humans with their interactions as well as their knowledge are the socio space, which is connected to the cyber and physical space by interaction or sensing.[129]

[121] Cf. Trotha et al. (2018, pp. 3232ff.).
[122] Cf. Lee, Bagheri, and Kao (2015, p. 20).
[123] Cf. Longo et al. (2017, p. 147).
[124] Cf. Barig and Balzereit (2019).
[125] Cf. Liagkou et al. (2019, p. 712).
[126] Cf. Yang and Plewe (2016, p. 283).
[127] Cf. Wang (2010).
[128] Cf. Smirnov et al. (2014, p. 101).
[129] Cf. Ansari, Khobreh et al. (2018, p. 91f.).

Cyber-physical-social production systems (CPSPS) organize human and machines in a production environment by tightening the cyber-physical-social interaction.[130] In terms of Industry 4.0, the concept of smart factories and Internet of Things are allocated into a cyber-physical system (CPS) and form a cyber-physical-social production system.[131]

With the increased usage of smart devices, equipment with built-in intelligence, a transition of a systems intelligence to all its underlying pieces of equipment is taking place. This allows the user to access data from anywhere at any given moment and lets the system organize and take decisions itself based on its predefined goals.[132] Production is more and more switching towards a high degree of individualization and moving away from standardized production processes. This rise in system complexity needs the flexibility and problem-solving ability of human workers so that in smart factories, people still play an important role and are not completely replaced by machines or smart systems. The support of human workers by the use of smart devices or work support systems enables an improvement in both their decision making and learning to cope with the increasing complexity of the tasks.[133] Basically, the concept of **smart factories** is based on the idea that humans and factories are connected in such a way that they interact and communicate so that their actions and production steps are synchronized.

The application of artificial intelligence in industrial applications is a key component of Industry 4.0. It represents the application of AI in an industrial environment. An **industrial AI** application consists of four technologies that are essential to a successful integration of AI.[134]

1) Data technologies: With AI techniques being based on the analysis of large amounts of sensor data, it is essential to collect useful data. Furthermore, the transfer of data is an important point as we have to deal with interaction and communication of machines, data storage in the cloud and communication between the cyber space and the physical space.[135]
2) Analytics technologies: The processing of the sensor data and discovery of patterns or correlations is performed by analytics technology. This helps making invisible relations visible and offers the possibility to the machine owner to react faster and better by knowing the effects of changes registered by machine sensors.

[130] Cf. Jiang et al. (2019 - 2019, p. 1402).
[131] Cf. Ding and Jiang (2018, p. 2323f.).
[132] Cf. Zuehlke (2010, p. 130).
[133] Cf. Uhlmann et al. (2019, p. 1418).
[134] Cf. Lee et al. (2018, p. 20f.).
[135] Cf. Lee, Ardakani et al. (2015, p. 5).

3) Platform technologies: They provide the hardware for the usage of the previously discussed tools. One distinguishes between embedded, stand-alone and cloud platforms. Cloud computing outsources the computation to a connected server. Embedded computing used to be operating as stand-alone systems, but with the rise of the IoT, more and more devices are being connected to the internet allowing embedded computing.[136]
4) Operations technologies: This refers to the communication between all kind of machines. This may be two machines on the shop floor or even two machines from the same manufacturer sharing experience on how to adjust certain settings to achieve better results.[137]

A major focus of AI applications is happening in the following fields based on the number of used cases:

- Predictive maintenance: Predictive maintenance uses and monitors the actual state of a machine by collecting machine data and using machine learning methods. The collected data is then used to derive an optimal maintenance schedule. There exist multiple monitoring methods that, if combined, offer a great variety of data that enables an in-depth analysis of the state of the machine. Main data sources are vibration monitoring, thermography, tribology, visual inspections or ultrasonics.[138] Predictive maintenance is more than simply applying the mentioned methods but consists of achieving a permanent good condition of the machinery as well as a high overall equipment effectiveness. The main steps of a predictive maintenance program are the data acquisition, the processing of the data and the maintenance decision making. The component that distinguishes predictive maintenance from other maintenance concepts is the usage of AI to detect the indicators that precede machine failures to react accordingly and prevent all kind of failures.[139]
- Quality inspection and assurance: To control the quality of the processed products, it is necessary for them to undergo a quality control. These kinds of controls are very often visual controls, which explains the interest in implementing automatic image processing. Manual inspection highly depends on the ability and concentration of the controller whereas automatic computer vision systems need to be trained once and are then able to operate by themselves. Depending on the data to analyse, supervised or unsupervised neural networks are used. The images are pre-processed to get rid of undesired visual effects and are then analysed using a machine learning approach. Main advantages over classic visual inspection are the ability to scale, lower rates of

[136] Cf. Furuichi and Yamada (2014, pp. 1605ff.).
[137] Cf. Lee et al. (2018, p. 22).
[138] Cf. Mobley (2002, pp. 99ff.).
[139] Cf. Selcuk (2017, p. 1670f.).

default parts as well as the ability to retrain the machine learning models in a short time.[140]

- Manufacturing process optimization: A major challenge in manufacturing systems is the rising amount of data that needs to be collected, analysed and manipulated.[141] Prerequisites for intelligent processes are mostly big data and knowledge-based intelligent technology.[142] Big data is necessary to ensure the development and availability of enough factors to optimize the system.
- Smart assistant: With smart assistants being mainly known in a smart home environment, they have a rising popularity in an industrial environment as well. The mainly used technology for smart assistants is automatic speech recognition in combination with a question answering system.[143] Speech recognition, especially real-time conversation, is an application of conversational AI. Industrial environments need applications that go further than simple chatbots but rather real-time applications with feedback loops that enable the AI model to learn from user interaction.[144]

2.5 Human and Machine Learning in CPSPS

The rising collaboration between human workers and machines creates the necessity for workers and machines to get trained for a proper functioning. A reduction of the number of workers in factories due to a higher level of automatization leaves the remaining workers with a higher degree of variance as the remaining tasks are distributed between a smaller number of people. The scope of the remaining tasks also switches from routine tasks that offer the possibility to learn on the job due to highly repetitive steps towards very specific tasks that are not performed on a regular basis.[145]

In cyber-physical social production systems (CPSPS), humans work alongside machines and scenarios occur that enable a learning process in which humans can learn from CPSPS or the system learns from the human.[146] Since machines are nowadays able to operate in an intelligent way, learning is not only unidirectional anymore.[147] Depending on the task, learning can be expressed as a **bidirectional learning process** that is happening between human and machine when performing a shared task.[148] In CPSPS, tasks may be assigned to a human, a machine or both, a shared task. During these shared tasks, a dependency between the two learning

[140] Cf. Chouchene et al. (2020, pp. 127ff.).
[141] Cf. Confalonieri et al. (2015, p. 2f.).
[142] Cf. Li et al. (2017, p. 95).
[143] Cf. Kovachki et al. (2020, pp. 1ff.).
[144] Cf. McCarthy (2019).
[145] Cf. Ansari, Hold, Mayrhofer et al. (2018).
[146] Cf. Ansari, Khobreh et al. (2018, p. 92).
[147] Cf. Ansari, Hold, Mayrhofer et al. (2018, p. 65).
[148] Cf. Ansari, Erol, and Sihn (2018).

partners is established and defines the **mutual learning** process.[149] Performance and quality have been identified as key indicators to measure the achieved learning performance.[150] It is possible to create a digital profile for both human workers and machines with the goal to identify and predict the learning trajectories of humans and machines. Their digital profile should contain personal information, technical specifications as well as data registered during their previous activities by sensors or other methods of feedback collection. Based on these profiles, an evaluation of the degree of automation of a workforce is easily possible. This helps with the role identification of the workforces in shared tasks.[151]

2.5.1 Decision Making in CPPS

'Human in the loop' describes the process when the machine is developing an algorithm and needs human intervention like involvement in the training and testing stages for creating a continuous feedback loop. This allows the algorithm to calculate every time better results.[152] At every iteration, feedback is saved by the robot and after several interactions and the analysis of the generated training data, the robot's behaviour is adapted. This is a so-called human-in-the-loop learning system as the behaviour of the human changes the robot's behaviour and the robot changes the behaviour of the human in terms of physical support.[153] In the human-in-the-loop approach, the decision taking is performed by the human. This represents a human-centred approach.

Important for the later skill matching is the classification of **human competence**. A valuable model for this has been developed by Dreyfus and offers us a valuable tool to classify human competences into five levels of competence.[154]

i. Novice: At the novice level, the task is decomposed into subtasks unrelated to the actual context, which makes it possible for the learner to perform or recognize without any specific skills but with simple given rules. It is important that the learner is not only given rules but also a context in which the given information make sense.
ii. Advanced Beginner: The advanced beginner understands the relevant context and discovers or gets informed of additional aspects of the domain. This requires some knowledge and understanding of the domain. Learning is still happening as the learner is given examples and following instructions.

[149] Cf. Goldberg (2019).
[150] Cf. Ansari, Erol, and Sihn (2018).
[151] Cf. Ansari, Hold, Mayrhofer et al. (2018).
[152] Cf. Singh Bisen (2020).
[153] Cf. Ikemoto et al. (2012).
[154] Cf. Dreyfus (2004).

iii. Competence: As the experience increases, the amount of relevant information and instructions is increasing as well. To master this huge quantity of information, the learner develops either by experience or because they are told how to filter important from unimportant information. As there are many situations that cannot be predicted or foreseen, the learner must decide for every decision individually as it is not possible to provide them with a set of rules for all possible situations. As a consequence, the outcome does not depend on a set of rules but on the learner's decision, which may result in failure or success.

iv. Proficiency: The learner gets more and more emotionally attached to the task so that a return to the rule-based decision making is not possible. The resulting negative and positive feedbacks from their decisions result in a decision where the right answer seems obvious to the learner.

v. Expertise: When seeing a task, the expert decomposes it immediately into a class of subtasks, which all require a specific action. This enables the expert to give the right situational response to the task.[155]

Over the recent years, **autonomy of production systems** has become increasingly important as it offers the possibility of production objects, tools or means of transportation that can store data and therefore communicate with the production system and make decisions on their own. With these means of interaction, new applications emerge, such as the prevention of quality problems by preventing the usage of the wrong tools for a specific workpiece or a more efficient problem management thanks to better and faster information regarding current or probable problems.

To classify a production system, the autonomy index AI is introduced. It represents the proportion of autonomous process steps to the total amount of process steps. A production system is autonomous if it acts self-determined. In this case, its degree of autonomy is 100. If none of the decisions are taken by the system, its degree of autonomy is 0.[156]

Systems can be classified in five categories based on their degree of autonomy:

i. Warning, Indication, Notification: Information of the user by an informational message or alert. In this case, the system is not autonomous as it is purely delivering information.

ii. Assistance: Like the previous category, the ability to assist cannot be classified as an autonomous property. The main task of assistance is to support human labor by providing information or resources during his task.

[155] Cf. Dreyfus (2004).
[156] Cf. Gronau and Theuer (2016).

iii. Partial Autonomy: With a small degree of autonomy, this category represents systems that overtake certain tasks from the human workforce.
iv. Conditional Autonomy: Under certain conditions and prerequisites, the system is performing tasks independently.
v. Full autonomy: This stage requires a degree of autonomy of 100. All actions are determined by the system without interaction with the human workforce.[157]

A task is defined in a working environment as an activity that needs to be performed by a worker to progress with their work. Although many tasks can be performed easier and faster due to the rise of automation and support systems, many remain very complex and require special knowledge and training.[158] **Task complexity** has been defined as an important factor influencing the performance of the task executioner and is therefore widely researched. It is essential to define the environment in which we are using task complexity. The complexity of a task can be subjective and in this case dependent on the worker or learner executing the task itself, relative when compared to another task or objective when focusing in the task properties.[159] To be clear in our definition of task complexity, we consider an objective perception of the complexity to ensure that it is measurable and comparable in our learning model. Several dimensions of complexity have been defined:

- Size: The size of a task is defined by its number of components.
- Variety: The variety can be determined by the differences of the task's components. A task with more components has a greater variety than a task composed of few components.
- Ambiguity: The ambiguity reflects the amount of unclear parts of the tasks. Parts that need further information to be solved or done.
- Relationship: The relationship is determined by the dependencies between the task components.
- Variability: A task is variable if parts are changing or if they are not stable.
- Unreliability: Unreliability refers to incorrect information that cannot be trusted.
- Novelty: Non-regular and new events or components affect the novelty of a task.
- Incongruity: The incongruity of a task is the amount of mismatches of its components. Tasks with a high amount of components have a high incongruity.
- Action complexity: A very important factor is the requirement of cognitive and physical abilities to solve a task.
- Temporal demand: The temporal demand represents any time-related constraints of a task.

[157] Cf. Ansari, Hold, and Sihn (2018).
[158] Cf. Wood (1986, p. 62).
[159] Cf. Campbell (1988, p. 43).

These dimensions are useful to define the complexity of a selected task and offer a great tool to select appropriate tasks in a learning environment.[160]

[160] Cf. Liu and Li (2012, pp. 553ff.).

3 State of the Art

To define the gap between theoretical concepts and up-to-date applications, the emphasis is put on how to measure the learning performance both for human learning and system improvements. After having investigated the existing learning assessment methods, the research gap between existing assessment methods and required methods for CPSPS should be closed with the development of a learning curve model.

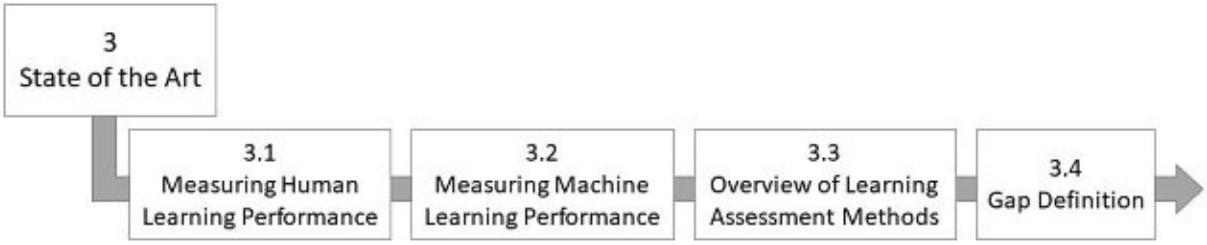

Figure 15: Structure of Chapter 3

The structure of this chapter is illustrated by Figure 15. Human learning and machine learning assessment methods are presented, followed by an overview of all the assessment methods and the gap definition.

3.1 Measuring Human Learning Performance

The learning process and its underlying processes in the human brain have widely been discussed in chapter 2.1. To determine if these activities in the human mind were successful and if the right stimuli have been created, it is necessary to measure the learning outcome. The most important and frequently used assessment methods are discussed in the following chapters.

3.1.1 Kirkpatrick Assessment Model

Training is necessary to reduce the gap between the required performance standard and the initial skill level.[161] The evaluation of the effectiveness is still an ongoing research as more models exist but only one is used in practice. The best-known model was introduced by Kirkpatrick in 1998. It identifies four levels to assess the learning performance.[162] The identified levels are:

- Emotional reaction: Learners who have performed a training and gained new skills are willing to apply them during their further work. Therefore, they will be showing a positive reaction. Questionnaires are useful to evaluate the learners' emotional state and derive from it the training effectiveness. Post-training

[161] Cf. McGuinness and Ortiz (2016, p. 253f.).
[162] Cf. Bates (2004, p. 341).

questionnaires have been criticised due to their accuracy and quality because the registered reactions are biased as they represent perceived and subjective evaluation of the training.

- Achievement of learning objectives: Learning objectives can be achieved through pre- and post-learning assessments. The improvement can be compared to benchmarks from which the learning effectiveness can be deducted. The big advantage is that this can be done with any kind of training.
- Behavioural changes: The behavioural level indicates how the information and skills gained are applied by the learner and how their performance and attitude is impacted. To evaluate the behavioural changes, peers and supervisors need to judge how the learner applies their new skills at work and how confident they are in sharing them with their co-workers as this explains how confident they are of their new abilities.
- Results: The fourth level consists of checking the results and the impact for the organization. This could be the influence on the production output, finances or KPIs. The measuring of the effect on an organization is very complex due to the high number of components and their interaction with their environment as this makes it very hard to predict the outcome of the learning process.[163]

[163] Cf. Alyahya Saad and Norsiah Bt. Mat (2013, pp. 2ff.).

3.1.2 Return of Invest (ROI)

This model is an extension of Kirkpatrick's evaluation model and was introduced by Phillips (1995).[164] Several aspects of the Kirkpatrick assessment model can be criticised, such as giving importance to the attendance of trainings or the personal attitude of the learner after the training which is a very subjective measurement. This is why a fifth level of the evaluation was added to the model, the return of investment (ROI). This fifth level builds up and evaluates the ratio between costs of the training and the program benefits.[165] The evaluation stage was born out of a business perspective and should be used to evaluate the business impact of learning.[166] The application of this model results in the following table displaying Phillips' five levels of evaluation.

Table 1: Phillip's five levels of evaluation[167]

Level	Brief description
1. Reaction and satisfaction	Measures participant's reaction to the program and stakeholder satisfaction with the program and the planned implementation
2. Learning	Measures skills, knowledge, or attitude changes related to the program and implementation
3. Application and implementation	Measures changes in behaviour on the job and specific application and implementation of the program
4. Business impact	Measure business impact changes related to the program
5. Return on investment	Compares the monetary value of the business impact with the costs for the program

3.1.3 Learning Transfer Evaluation Model

In order to improve the drawbacks of Kirkpatrick's assessment model that are outlined above, a new model has been proposed by Thalheimer, which is based on eight tiers, decreasing from top level representing good methods of evaluation towards the lowest level representing bad evaluation methods. The tiers are described in the following points.[168]

[164] Cf. Phillips and Phillips (2001, p. 242).
[165] Cf. Schmitz and Holling (2010, p. 238).
[166] Cf. Phillips and Phillips (2001, p. 242).
[167] Phillips and Phillips (2001, p. 242).
[168] Cf. Talheimer (2018).

1) Attendance: Some organizations are issuing certificates to learners for only participating in a training, without being required to prove any activity or gained knowledge. These kinds of metrics are almost useless in evaluating the learning performance.
2) Activity: A learner's activity can be measured by their attention, interest or participation during the training, especially when using digital tools for capturing the training. Although this does not prove any learning, it can be a good indicator for design quality of the learning program.
3) Learner Perceptions: By using surveys or feedback sheets, capturing the learner's perceptions about the performed training is an easy task and therefore widely used in practice. The downside of this method is that questions asking about the learning effectiveness are mostly creating proxies, such as asking about the level of realistic practice having received being a proxy for long-term remembering.
4) Knowledge: Knowledge can be tested very shortly after the learning experience or after a certain time. Testing after a short delay puts a focus on facts and terminology, which is unlikely to enable task competence. The better way of measuring is therefore testing after a delay which focuses more on the more natural way of remembering although it as well largely focuses on terminology and the knowledge of facts.
5) Decision Making Competence: An important goal of learning should always be to improve the decision-making competence of the learner. Consequently, decision making should be assessed. To do so, a possibility is to confront the learner with realistic scenarios that require them to take realistic decisions. These scenarios can be simulated in various ways, they can be text-based, digital or even a role-play.
6) Task Competence: The demonstration of a strong task competence represents a high learning effect, but it is important to assure that the task competence can be demonstrated even a certain time after learning. Task competence can be measured by exposing the learners to realistic situations, let them evaluate the situation, make decisions, and take actions accordingly.
7) Transfer: One distinguishes between two kinds of transfer, assisted transfer and full transfer. Assisted transfer represents the application of learned knowledge during the job with assistance or support. Full transfer represents the transfer of their learning to the job.
8) Effects of Transfer: The effects of transfer are the penultimate goal of the learning process. The goal of learning is not only to transfer the learnt knowledge on the job but to get a better outcome in the end. To measure the

effects of transfer, the evaluation of KPIs or other production indicators represents a good tool.[169]

3.1.4 Transfer Process Model

Besides the main theory of Kirkpatrick, there emerged another theory by Baldwin and Ford (1988) in which the importance of transfer in trainings was highlighted. The process which is shown consists of training input factors, training outputs and conditions of the transfer. Input factors consist of design principles, trainee characteristics and the work environment shown in Figure 16: Transfer process model. This model takes in consideration intrapersonal as well as external factors on the trainings and has a more holistic access towards evaluation. Furthermore, the output is defined as the learned content and what was kept.[170] The core of this theory are the two conditions which determine the transfer. The first factor is the generalizability of the learned content on the job, whereas the second factor mentioned is maintenance of the learned contents over time, basically the holding up on the content and not losing it. Both factors are also influenced indirectly by outcome and input factors. In the literature, this model has often been referred to as the most influential framework for evaluating training transfer.[171] There has been intense research which factors are the most influential and several could be validated.[172] The trainee characteristics which were most influential were cognitive ability, self-efficacy, motivation and perceived utility of the training. Influences on the training design therefore were behavioural modelling, error management and realistic training environments. The work environment was extended in this paper by transfer climate, support, opportunity to perform and follow-up.[173] As shown before, most factors of the original model could be validated although the model was extended by newer models as self-efficacy and the follow-up of trainings.

[169] Cf. Talheimer (2018, pp. 11ff.).
[170] Cf. Grossman and Salas (2011, pp. 105ff.).
[171] Cf. Blume et al. (2010, pp. 1068ff.).
[172] Cf. Grossman and Salas (2011, pp. 104ff.).
[173] Cf. Grossman and Salas (2011, p. 116f.).

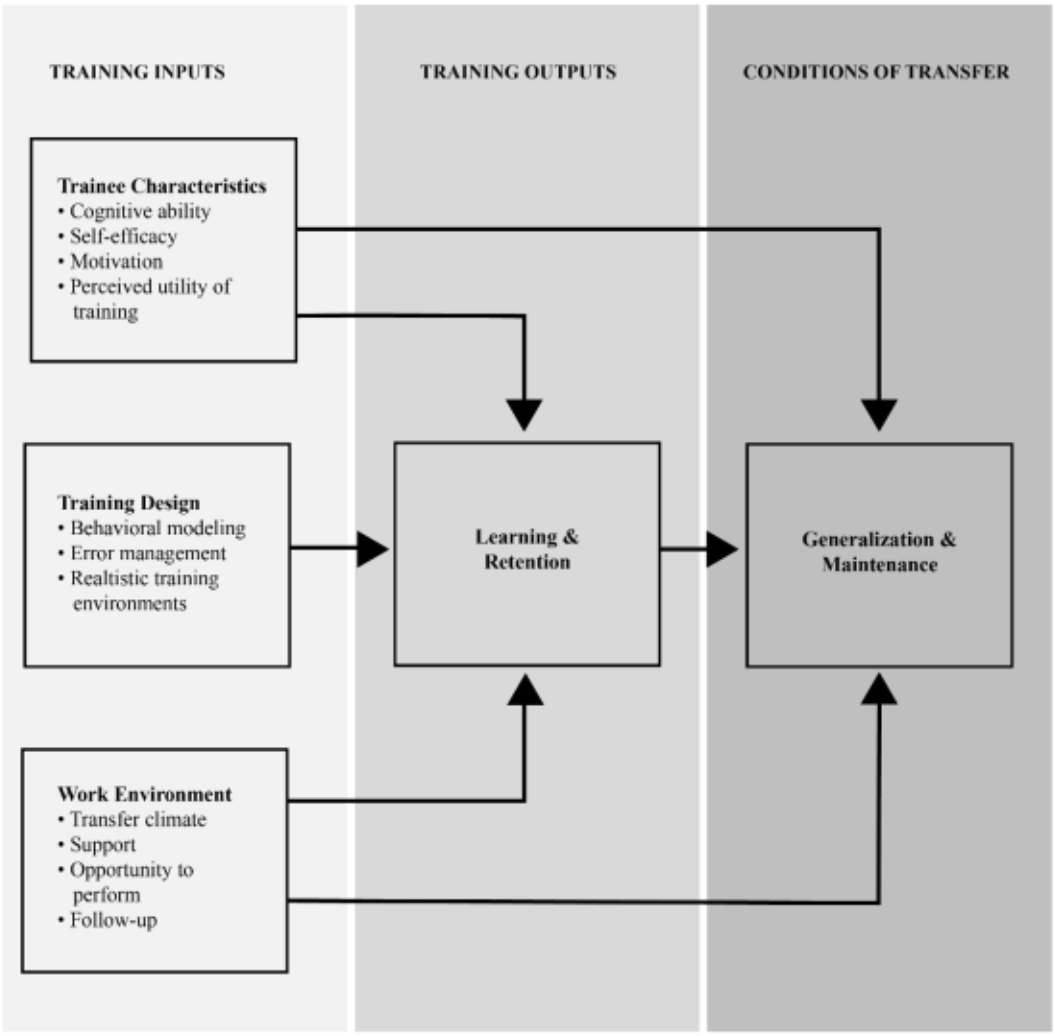

Figure 16: Transfer process model[174]

3.1.5 Ontology-Based Evaluation Tool

Training data is collected at the shop floor and later analysed by an analytics tool that creates summaries describing the workers' level of expertise. The tool is based on a training data evaluation ontology which produces a semantic-driven classification of the learners' expertise using semantic web languages. Therefore, the tool is extended with four domain-specific ontologies. Those are used for 1) the evaluation of training activities, 2) the classification of the training results regarding KPIs, 3) the classification of the training results regarding the Kirkpatrick model elaborated in 3.1.1 and 4) the training impact.[175]

After the data evaluation ontology, the training analytics model addresses the evaluation of the training and the skill classification. For each level of Kirkpatrick's

[174] Grossman and Salas (2011, p. 106).
[175] Cf. Arena et al. (2018, p. 221).

model, a set of KPIs is developed to compare against the data from the workshop and a tool to assign a competence level to every learner based on their performance compared to other learners.[176]

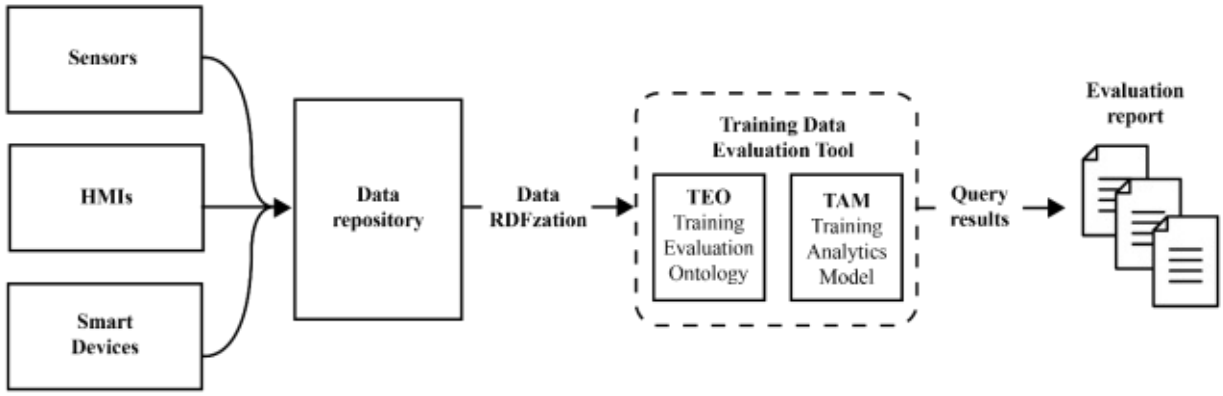

Figure 17: Architecture of the training data evaluation tool[177]

3.1.6 Evaluation for Learner-Controlled Trainings

Learner-controlled trainings offer the possibility for the learner to adapt the learning to their own requirements. The training can be adapted regarding the learning style, knowledge levels and abilities of the learner. Learner control means that learners themselves have the autonomy to control the speed of their own learning progress.[178] Very often, these trainings take place in an e-learning environment. Improved affective reactions and a greater commitment to attend further trainings are the benefits of giving control to the learner.[179] The evaluation of learner-controlled trainings is based on the Kirkpatrick model. In this case, the focus lies on the reactions to and the learning outcomes of the training.

To measure training satisfaction, surveys at the end of the training are used. The disadvantage of the subjectivity of surveys has already been discussed earlier. A better method is used to measure training performance, where a test at the end of the training is a valid method to evaluate the achieved level of performance. Interactive websites are very favourable towards increasing retention of the learnt material. Self-efficacy represents the belief of the learners in themselves, which offers a good tool to estimate the applicable skills.[180]

[176] Cf. Perini et al. (2017, pp. 314ff.).
[177] Perini et al. (2017, p. 317).
[178] Cf. Friend and Cole (1990, p. 47).
[179] Cf. Kraiger and Jerden (2007, p. 67).
[180] Cf. Abraham and Chengalur-Smith (2019, pp. 2ff.).

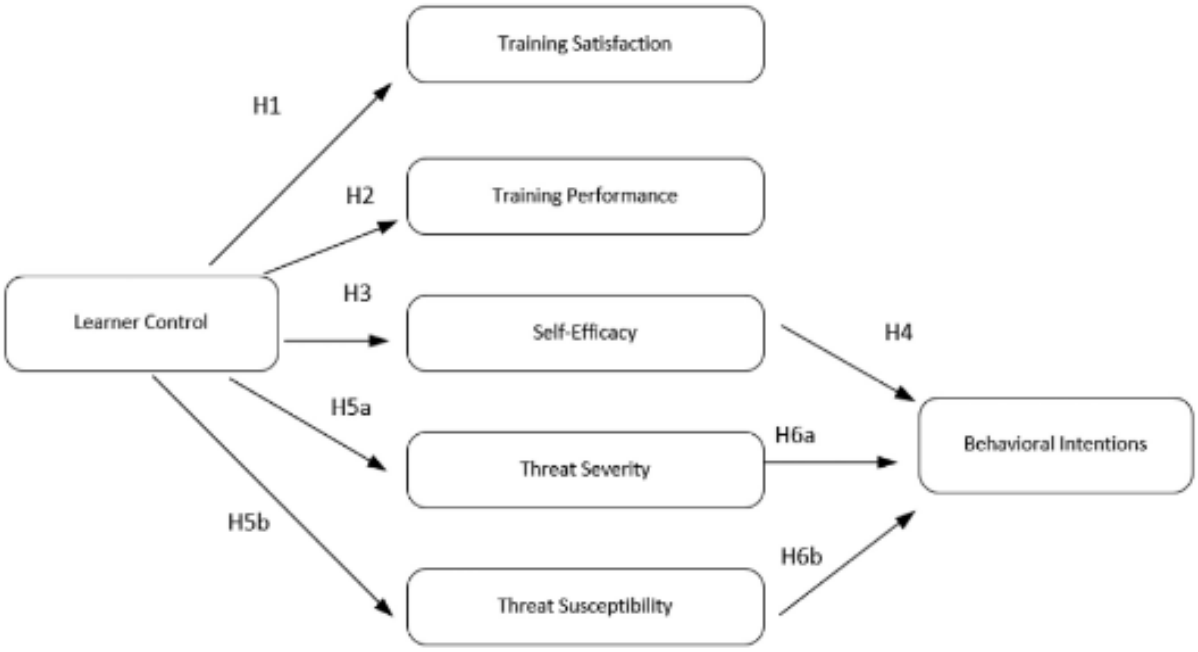

Figure 18: Model for learner-controlled trainings[181]

3.2 Measuring Machine Learning Performance

As this thesis is focusing on human-centred learning, we briefly elaborate on the ways how to measure the machine learning performance. Measuring a machine learning performance is performed by tools that are widely applied in practice.

3.2.1 Confusion Matrix

The confusion matrix is a common tool used to describe the effectiveness of an algorithm. In the case of a binary problem with the labels positive and negative, the confusion matrix would have the following appearance, where t_p would be the amount of examples with the label positive that were predicted correct by the algorithm, f_p would be the amount of examples with the label positive that were predicted falsely by the algorithm, t_n would be the amount of examples with the label negative that were predicted correct by the algorithm and f_n would be the amount of examples with the label negative that were predicted falsely by the algorithm.

$$\begin{bmatrix} t_p & f_n \\ f_p & t_n \end{bmatrix}$$

Figure 19: Confusion matrix

[181] Abraham and Chengalur-Smith (2019, p. 5).

In order to improve the algorithm, one should strive to maximize the values of the primary diagonal and minimize the other ones. The dimension of the matrix is n*n, where n represents the amount of possible results of the algorithm.[182]

3.2.2 Loss Function

The loss function, sometimes also called error function, is a method for an algorithm to detect and select the curve that fits the analysed data the best way. If the actual model deviates too much from the analysed data, the loss function emits a large number. On the other side, it is possible to minimize the loss function by detecting the best values for the parameters a and b of the loss function shown in Formula 8.

$$L = \sum (y_i^{true} - y_i^{pred})^2 = \sum [y_i^{true} - (a * x_i + b)]^2$$

Formula 8: Loss function

The optimization of the loss function is commonly done by an ordinary least squares method. The goal is to minimize the deviation between the predicted and real values.[183]

3.2.3 Number of Iterations

In the area of machine learning, a learning curve describes the number of iterations that are needed to achieve a certain percentage of accuracy.[184] Figure 20 shows a typical learning curve that is used to determine how many iterations a certain algorithm needs to learn. The x-axis shows the number of iterations and the y-axis the accuracy.

[182] Cf. Nguyen and Zeigermann (2018, p. 130f.).
[183] Cf. Nguyen and Zeigermann (2018, p. 65f.).
[184] Cf. Sammut and Webb (2011, pp. 578ff.).

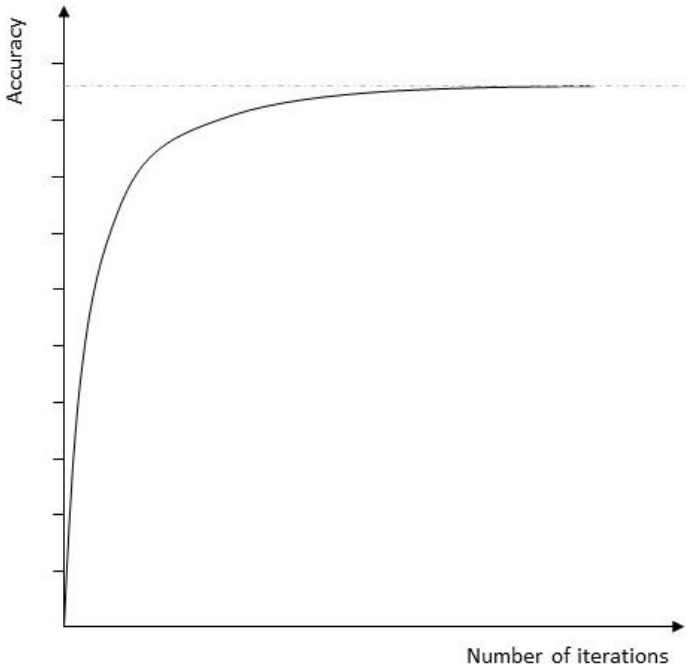

Figure 20: Typical learning curve for machine learning

3.3 Overview of Learning Assessment Methods

An overview of the researched Assessment Methods of this chapter is included in Table 2. It provides the application possibilities such as the evaluation techniques and the focus of the assessment. To summarize, one can say that the predominant model is Kirkpatrick's assessment model. Most of the models analysed are based on this model. Some newer models such as the ontology-based assessment model focus on the evaluation of the training activities and classify their results regarding selected KPIs to create a link towards a measurable indicator. However, these models are outnumbered by models that still rely on post assessment using surveys and tests.

Table 2: Learning assessment methods

	Learning assessment method	Details
Human Learning	Kirkpatrick assessment model	• Evaluation of: ○ Emotional reaction ○ Achievement of learning objectives ○ Behavioural changes ○ Results • Evaluation techniques ○ Post training questionnaires ○ Pre and post learning assessment ○ Peer and supervision judgement KPI measurement

	Learning assessment method	Details
Human Learning	Return of invest (ROI)	• Evaluation of: ○ Reaction and satisfaction ○ Learning ○ Application and Implementation ○ Business impact ○ Return of investment
	Learning transfer evaluation model	• Evaluation of: ○ Attendance ○ Activity ○ Learner ○ Knowledge ○ Decision making competence ○ Task competence ○ Knowledge transfer ○ Effects of transfer
	Transfer process model	• Evaluation of: ○ Trainee characteristics ○ Training design ○ Work environment
	Ontology-based evaluation tool	• Evaluation of: ○ Training activities • Classification of the results regarding: ○ KPIs ○ Kirkpatrick Model ○ Training impact
Machine Learning	Confusion matrix	• Evaluation of: ○ True positive predictions ○ True negative predictions ○ False positive predictions ○ False negative predictions
	Loss function	• Evaluation of: ○ Result of the loss function • Optimization through: ○ Minimization of the least squares between predicted and measured values
	Number of iterations	• Evaluation of: ○ Time/number of iterations to reach a certain accuracy

3.4 Gap Definition

An overview of the models to evaluate the learning process has been presented in chapter 3.3. When applying these methods to the processes in a smart factory, it

becomes obvious that they do not meet the necessary requirements of the CPSPS learning processes discussed in chapter 2.5. Assessment methods used in CPSPS need to be responsive as the need to adapt to changing interactions between humans and machines. Furthermore, the high amount of decision taking and changing tasks requires the assessment to consider all available factors. Surveys and tests are present in a multitude of assessment methods but may have problems to target the learning process in CPSPS as it is not an unidirectional process.

None of the researched models take into account the external factors influencing the learning progress or offer the possibility to predict the outcome of learning measures taken. Post analysis supports the evaluation of learning outcomes but requires excessive resources and can only be done after the training. To evaluate the effect of changes in the production environment, manufacturers are required to test before they are able to see the effect on their production outcome. A way to predict the learning outcome by analysing the influencing factors before the actual learning process is missing. This could enable to predict the changes in the processes where learning takes place and would lead to a better plannability of the effects of changing conditions. To fill this gap, in this thesis a model that enables us to simulate the learning process and derive the impacts is proposed.

4 Predictive Model Development

The analysis of the learning theories as well as the presented methods to evaluate the learning progress made it clear that it is essential to know how training and learning affect the performance in an industrial environment. So far, the evaluation of learning effects is taking place after the learning progress. This results in excessive time consumption to determine how external changes are influencing the learning process. To tackle this issue, a model that predicts the learning outcome through prediction of the learning curve is developed. After the validation for a specific use case, the model can easily be adapted to similar applications without the need of further validation.

The methodology chosen for the development of the learning model reflects the idea of the design science research process described in 1.4. After having defined the problem, the next step is to develop a solution by building an artefact.

4.1 Methodology of the Model Development

The methodology of the model development can be described in four steps and is shown in Figure 21. First of all, data collection is performed by the collection of scientific studies examining the effect of influencing factors on the learning curve. Depending on the quality of the collected data, it needs to be cleaned, transformed or processed. When the data is available, it is possible to derive a learning curve for every influencing factor. The goal of the derivation for every single factor is the comparability between the factors and the integration into a common model.

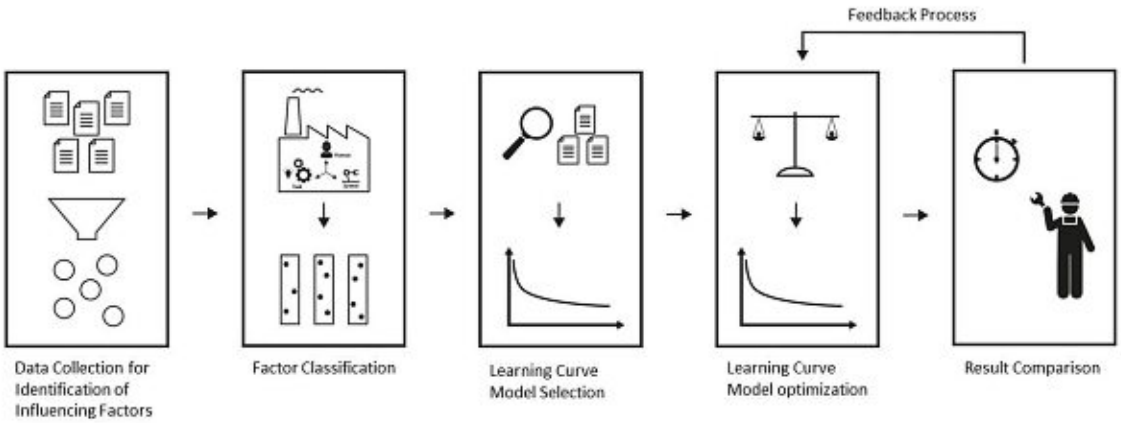

Figure 21: Methodology of the Model Development

The second step consists of a classification of the factors into previously defined categories. The selection of the categories is based on research papers dealing with cyber-physical production systems and elaborated through research about learning.

Step three is the selection of a suitable learning curve model based on existing learning models including the possibility to include the researched factors. A study and

evaluation of existing learning curve models is performed. Advantages and disadvantages are discussed. Based on the evaluation, a suitable model is selected and adapted to meet the requirements of a predictive learning model taking into accounts multiple factors.

An analytical hierarchy process is used to optimize the developed model. The weight factors of the selected influencing factors and the classifiers are calculated in this step. The analytical hierarchy process is a multicriteria decision process developed by the mathematician Thomas Saaty. Available characteristics are taken into account and compared against each other. This is done by establishing a hierarchy which decomposes the problem into various levels of criteria starting with the first criteria and adding sub-criteria beneath, comparable to a tree structure. All elements of every level are being compared one to another. The theoretical part of the analytical hierarchy process is explained in chapter 4.5 including the factor comparison and the calculation of the weights.

To correct and fine-tune the model, a feedback control loop is introduced. The aim of the control loop is to correct potential errors in the pairwise comparison based on the obtained results. The control loop is optional and can be neglected in case of sufficient quality of the obtained results.

4.2 Derivation of the Learning Rate for the Influencing Factors

As the learning curve links factors to performance indicators, it is essential to determine and analyse the influence of each factor on the learning curve. In a later step, these are combined to establish a single relationship between the factors and the learning curve. For every factor, the relationship is based on datapoints or formulas established in previous scientific papers. As described in chapter 2.2, the slope of the learning rate is calculated for every factor.

Table 3: Factor overview

Factor	Description
Economies of learning	Gain in output due to increased experience
Type of production technology	Production method used
Task variety	Diversity of performed tasks
Team composition	Group composition of task solvers
Experience	Abilities and knowledge gained through previous activities
Forgetting and lot size	Loss of ability caused by inactivity
Work and learning assistance system	Digital or physical system supporting work tasks or learning

i. Economies of learning

The amount of repetitions determines the value of the learning curve as the number of repetitions are representing the x-value of the learning curve chart. The larger the chosen number of repetitions, the more the learning curve approaches a delimiter asymptote which represents the best possible time to perform the chosen task. Economies of learning differs from the other influencing factors by not having an influence on the shape of the learning curve. Instead, it defines the evaluation point of the learning curve and is therefore essential to calculate a numerical change along the learning curve.

ii. Type of production technology

As described in 4.2, the production technology influences the progress ratio and therefore the learning rate. The following data has been adopted from Hirsch (1956)

and is used to extract the learning ratio as well as to derive the slope of the learning curve.[185]

Table 4: Assembly and machining progress ratios

Product	Assembly progress ratio [%]	Machine progress ratio [%]
Semi-automatic turret lathe #1	27.5	6.4
Semi-automatic turret lathe #2	30.8	20.2
Automatic machine tool #1	25.5	13.2
Automatic machine tool #2	28.6	14.1
Automatic machine tool #3	23.7	10.4
Automatic machine tool #4	23.2	13.5
Multiple purpose construction machine	19.0	20.1
Mean of 7 products	25.6	14.1

The mean value of both ratios is 25.6% for assembling and 14.1% for machining. The following slopes are calculated from the values in Table 4.

Assembly:

$$LR = 1 - PR = 1 - 0.256 = 0.744$$

$$b = \frac{\log LR}{\log 2} = \frac{\log 0.744}{\log 2} = -0.427$$

Manufacturing:

$$LR = 1 - PR = 1 - 0.141 = 0.859$$

$$b = \frac{\log LR}{\log 2} = \frac{\log 0.859}{\log 2} = -0.219$$

Graphically, the impact of the learning rates can clearly be seen in Figure 22: Learning curves for different production technologies. Both curves starting with an average time per unit of 100 chosen as initial value. The assembly learning curve has

[185] Cf. Hirsch (1956).

a much steeper slope than the manufacturing curve, which results in an average time per unit of 36.4% of the initial value for the 100th output in the case of manufacturing tasks and 14% for assembly tasks.

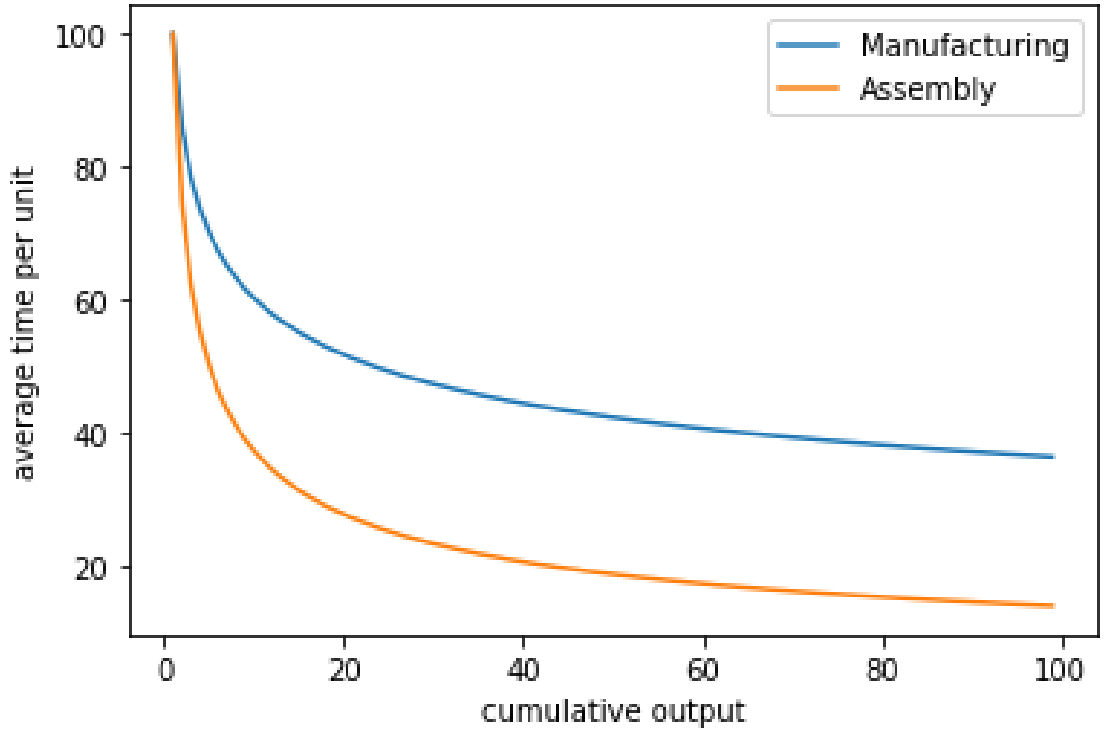

Figure 22: Learning curves for different production technologies

iii. Task variety

The learning curve has a specific form depending on the variety included in the performed task. Specialized and unrelated tasks have a smaller learning effect than related tasks as they enable the learner to acquire similar and useful knowledge in other domains that can be used for similar tasks in another environment. Schilling, Vidal et al. (2003) investigated this phenomenon by studying the impact of related tasks in gameplay. Their study observed teams composed of three people playing Go, an abstract strategic board game in which a score between 0 and 169 points can be achieved, against a virtual opponent. A third of the subjects additionally played Reversi, a related game which is similar in appearance and objectives. As an unrelated version Cribbage was used, which is more reliant on mathematical skills compared to Go and Reversi which are mainly reliant on special skills. The last third of the subjects specialized in Go and did not play any other games. The dependent variable in their experiment was the score achieved in every game of Go played. The slope of the learning curve was determined by plotting the achieved score over the number of times the game was played.[186] This results in a positive slope. We used the negative value

[186] Cf. Schilling et al. (2003, p. 51).

to calculate the learning rate by applying Formula 1. Figure 23: was added to visualize the differences and the impact on the learning curve.

Table 5: Slopes for researched task varieties

Group	Slope b	Learning rate
Specialization	0.14	0.935
Unrelated variation	0.21	0.904
Related variation	0.4	0.825

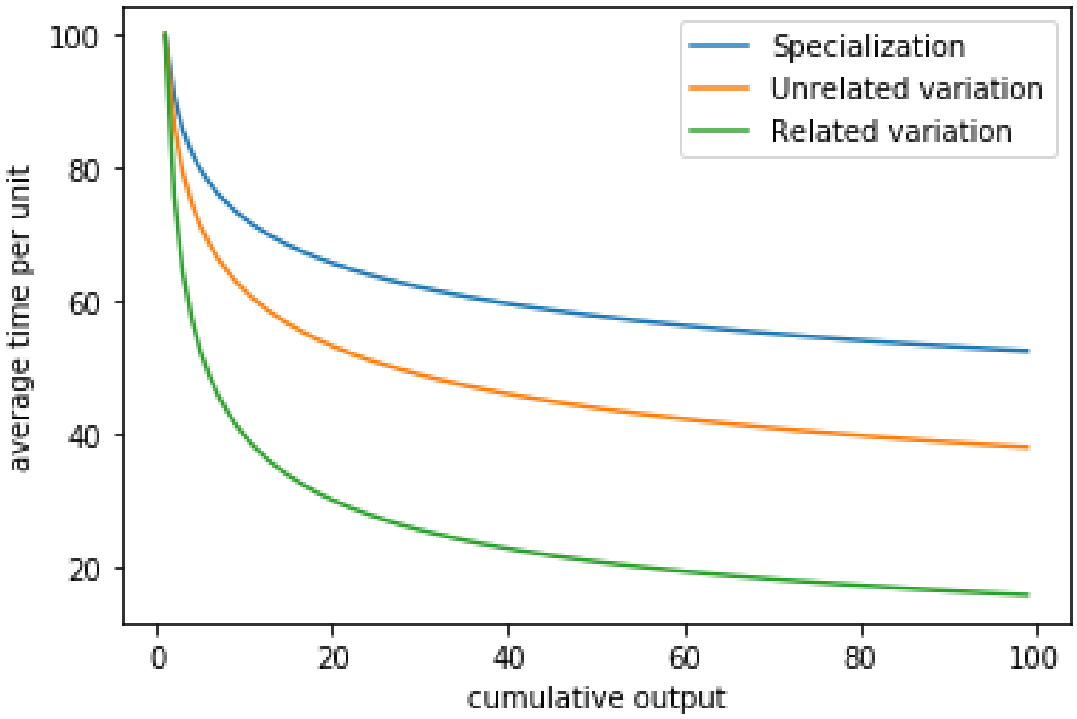

Figure 23: Learning curves for different task varieties

iv. Team composition

To test the effects of team composition on the individual learning curve, Boh, Slaughter and Espinosa (2007) conducted research into the effect of team composition in software development. They investigated how the experience of team members affects the individual learning when working on the same task as it was assumed that team members with a more diverse experience are coming up with more innovative solutions by integrating previously acquired knowledge compared to team members with specialized knowledge. To prove this assumption, they tested teams working in software development by conducting a field study of large-scale systems development in the telecommunications industry. To evaluate learning, the examined modification requests, which are used to add new functions or modify existing functions and code,

were used as the unit of analysis. After being reviewed and approved, several modification requests are grouped and represent a new release.[187]

The following results were obtained for the examined factors with the corresponding learning rate according to Formula 1:

Table 6: Slopes for different team compositions

Group	Learning slope b	Learning rate
Average group same-system experience	−0.024	0.988
Average group related systems experience	−0.034	0.984
Average group unrelated systems experience	−0.016	0.992

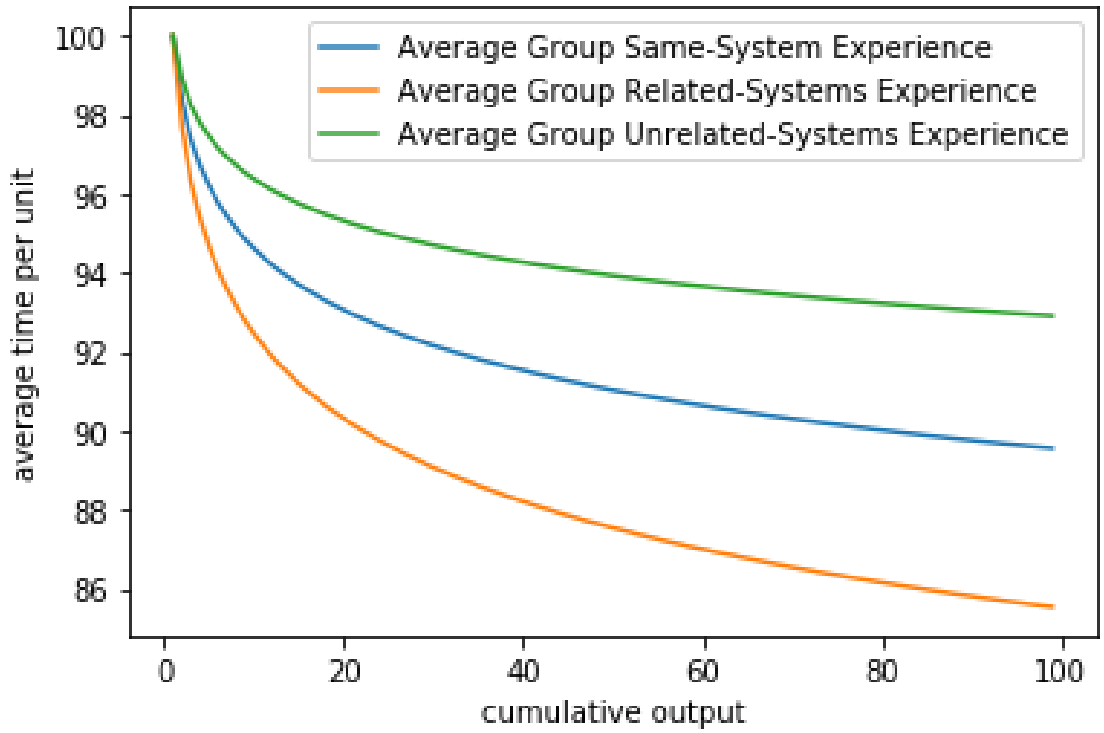

Figure 24: Impact of team composition on the learning curve

v. Experience

Experience of the individual learner is another factor that has been examined in the study discussed in the previous point as people with experience learn in a different way than people without previous knowledge in the same or another domain. Over time, people learn how to learn and how to process information and structure

[187] Cf. Fong Boh et al. (2007, pp. 1320ff.).

knowledge.[188] Therefore, it is assumed that people with further experience in group collaboration have a steeper learning curve than unexperienced learners.

Table 7: Slopes for different individual experiences

Group	Learning slope b	Learning rate
Individual same-system experience	−0.034	0.988
Individual related systems experience	−0.025	0.984
Individual unrelated systems experience	−0.007	0.997
Individual experience working with others	−0.016	0.992

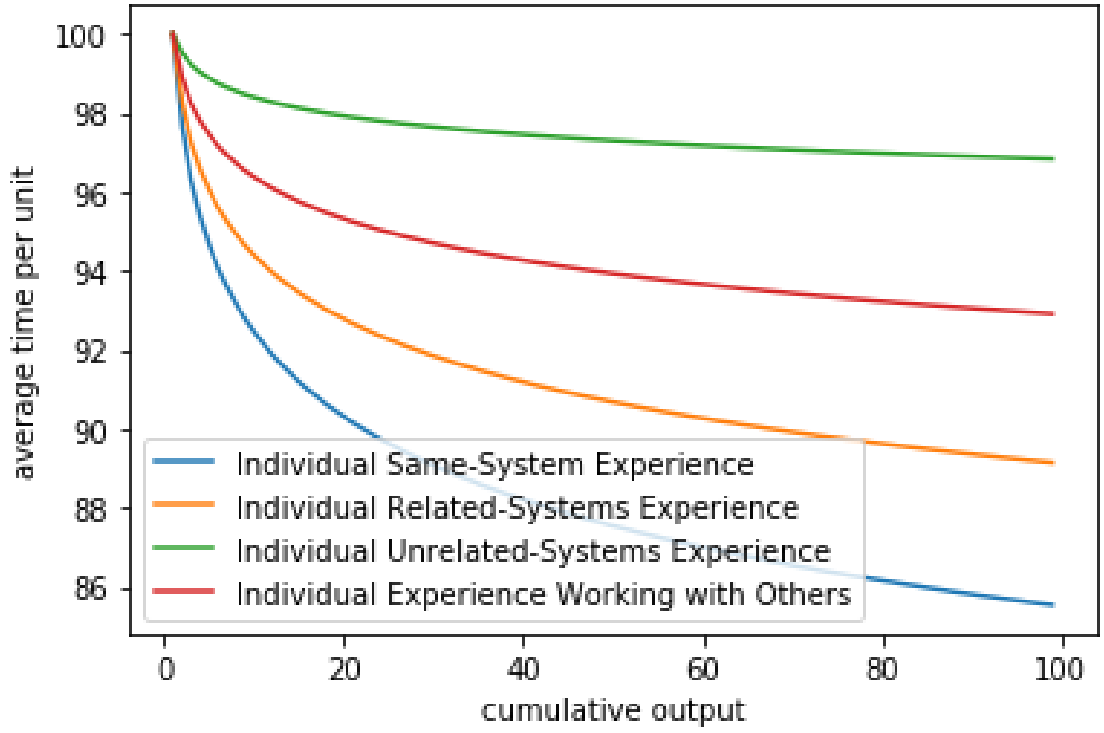

Figure 25: Impact of individual experience on the learning curve

vi. Ratio of cognitive to motor tasks

The learning takes place when performing motor tasks compared to performing cognitive tasks. Therefore, this should be handled separately when applying the learning curve. A proposition of Dar-El (1995) was to define the slope of the dual phase learning curve model as following:

[188] Cf. Fong Boh et al. (2007, pp. 1320ff.).

$$b^* = b(n) = b_c - \frac{\log(\frac{R + n^{b_c - b_m}}{R + 1})}{\log(n)}$$

Formula 9: Slope of the dual phase learning curve model

Here, T_1^c is the time to perform the first repetition under pure cognitive conditions, T_1^m under pure motor conditions, b_c is the learning exponent under pure cognitive conditions, b_m under pure motor conditions and $R = T_1^c / T_1^m$. Based on empirical data, they identified the learning exponents as $b_c = 0.514$ which equals a learning rate of 70% and $b_m = 0.152$ which equals a learning rate of 90%.[189]

Jaber and Glock improved the dual phase learning model and introduced the following Jaber-Glock model:[190]

$$T_n = xT_1 n^{-b_c} + (1 - x)T_1 n^{-b_m} = T_1[x(n^{-b_c} - n^{-b_m}) + n^{-b_m}]$$

Formula 10: Jaber-Glock learning curve model[191]

Here, x represents the percentage of splitting the task into a motor and cognitive task whereas n is the number of repetitions or the cumulative output in the learning curve. Figure 26 shows the learning curves for selected ratios of cognitive to motor tasks.

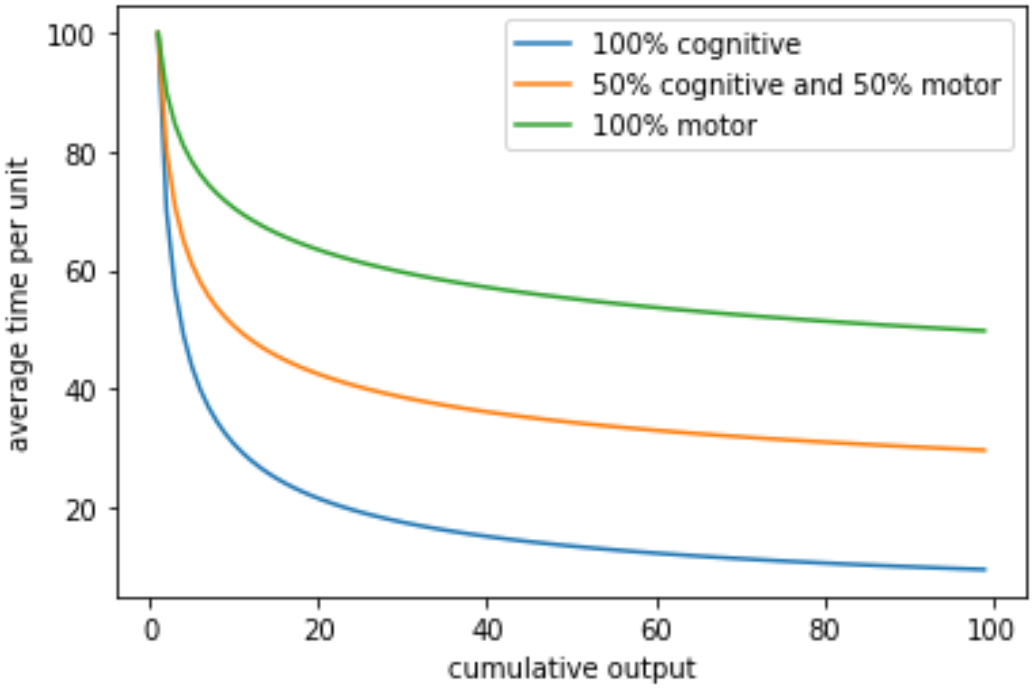

Figure 26: Learning curves for different ratios of motor and cognitive tasks

[189] Cf. Dar-el et al. (1995, p. 271).
[190] Cf. Jaber and Glock (2013).
[191] Jaber and Glock (2013).

vii. Forgetting and lot size

The theory behind the learn forget curve model has been explained in chapter 2.2.4. The plotted LFCM is shown in Figure 27.

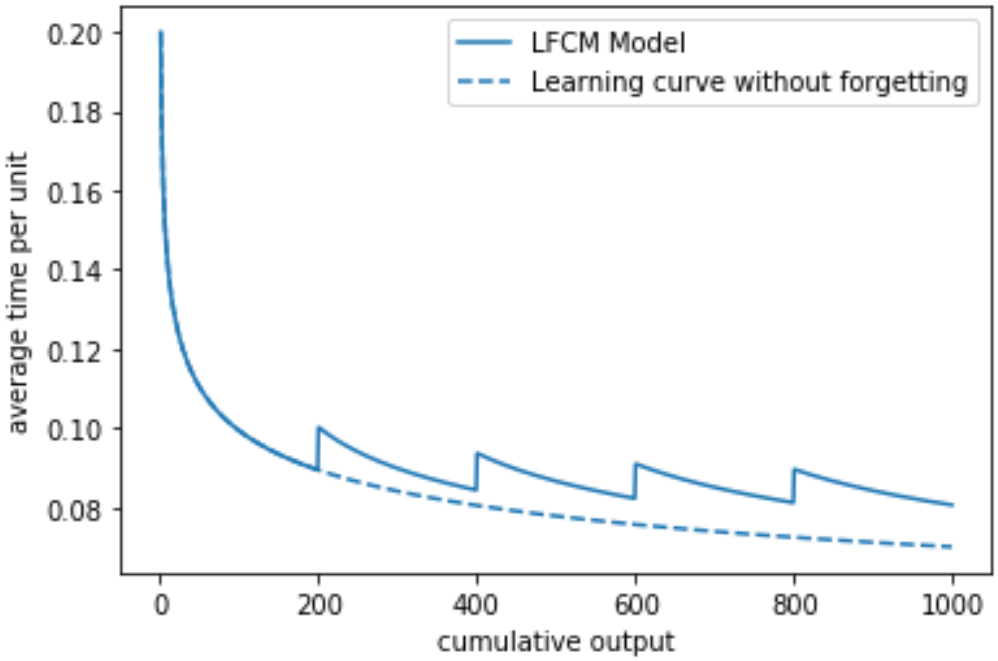

Figure 27: LFCM model

Figure 27 clearly shows the rise in production time during the breaks when forgetting occurs. The initial value of the production time was selected to be 0.2 days with a lot size of 200 units, a break time of 10 days and a total forgetting period of 300 days. To be able to compare the LFCM to the log-linear curve without forgetting and to use it in an own developed model, it is necessary to generate a comparable curve. By fitting an exponential curve to the data points generated out of the LFCM, an approximation is created. The results of the curve fitting, using a least squares method, are shown in Figure 28. Learning slopes of curves with forgetting and learning slopes of curves without forgetting can easily be compared in that way. The learning slope of the learning curve without forgetting is −0.152 whereas the fitted learning curve has a slope of −0.135.

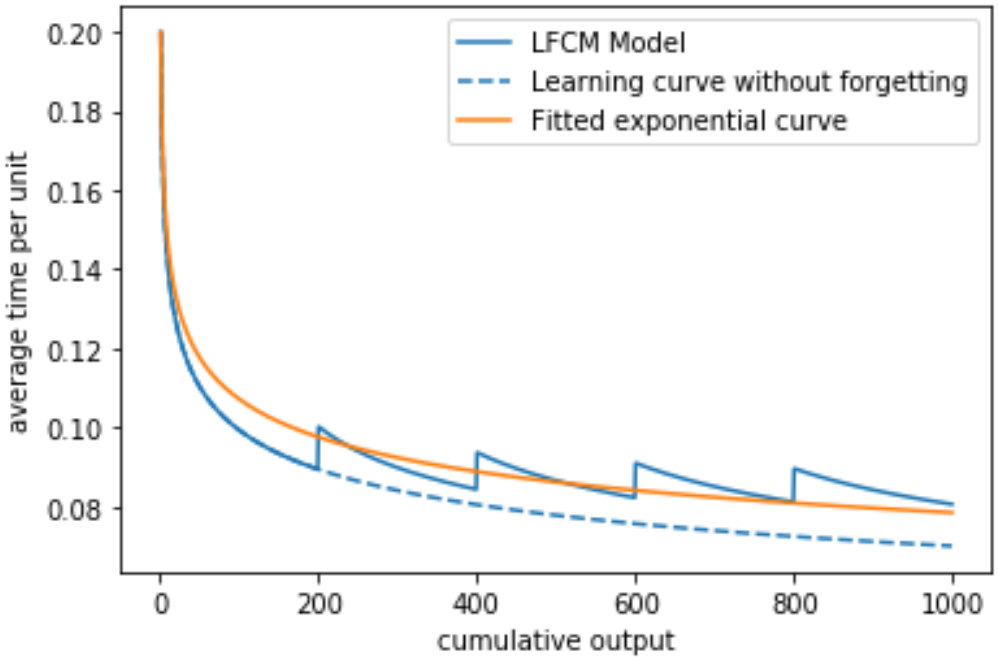

Figure 28: Fitted exponential curve.

viii. Work and learning assistance systems

Usage of learning assistance systems was researched by Longo, Nicoletti and Padovano (2017) by testing an operator support system in manufacturing which consists of a system that provides operators with real-time feedback, support for tasks and procedures in terms of augmented reality content as well as supporting the operators with an assistant that provides them with data and information about components, machines, tasks and processes.[192] The advantage of the system consists in the multitude of sensors and devices that can be used as input or output devices. Therefore, it is scalable and modular for further usage. In the discussed case, the system has been used for the usage of a CNC drilling machine by recreating a virtual model and importing all the important resources, which were then used to develop augmented reality content for maintenance procedures. The proposed support for maintenance operations includes most parts of the CNC machine such as pneumatic/hydraulic systems, filters, axis, electrical system, spindle/transmission etc. Two groups of operators were formed with ten operators each, the first group underwent traditional training and the second group was trained by the system. Afterwards, they had to produce batches of 100 low carbon steel bars. Their time needed for a batch was then measured and used to derive a learning curve. The used learning curve was of the following form, where Y_i is the cumulative average setup time, B_0 is the asymptote that represents the minimum achievable setup time, B_1 the average setup time for the first batch and B_2 the learning slope.

[192] Cf. Longo et al. (2017).

$$Y_i = B_0 + B_1 x^{-B_2}$$

Formula 11: Learning curve model[193]

For the traditional training, a learning rate of 91.85% was calculated, whereas a learning rate of 89.82% was achieved for the training supported by the support system. The results are displayed in Figure 29.

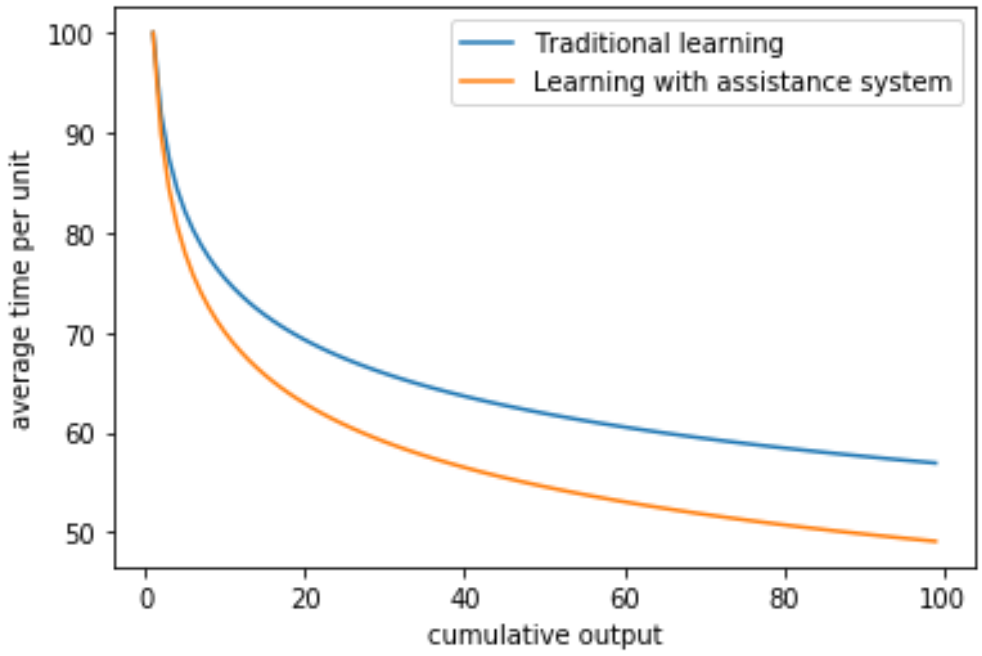

Figure 29: Influence of a learning assistance system on the learning curve

4.3 Factor Classification

Decision taking has an impact on learning.[194] To be compliant with research performed by Ansari et al. (2018), decision making in cyber-physical production systems is performed by both humans and the system. The decision making in CPPS was described by the vector of competence and autonomy. It is linking human competence with the degree of automation of a CPPS.[195] Human competence and the degree of autonomy of systems decide about decision takers. The vector of competence and autonomy is introduced.[196] All the levels of human competence and the degree of autonomy of a system are explained in 2.5.1.

Learning in production processes is dependent on the tasks performed.[197] Ansari et al. (2018) concluded that the performed task has an impact on the art of learning. In a

[193] Towill and Cherrington (1994).
[194] Cf. Bettis-Outland (2012).
[195] Cf. Ansari, Hold, and Sihn (2018, p. 223).
[196] Cf. Ansari, Erol, and Sihn (2018, p. 223).
[197] Cf. Kirschner et al. (2011, p. 620).

smart factory, tasks can be performed by humans, machines or being shared task and have a direct impact on the learning process between human and machine.[198]

To be compliant with research and to consider all parameters having an influence on the learning curve in a CPPS, the task parameter is included into the developed learning curve model.

By classifying the factors based on their influence on the learning curve, we are able to provide a simple and comprehensible model. The classification of the factors into one of the three categories human, system or task provides the classification shown in Figure 30.

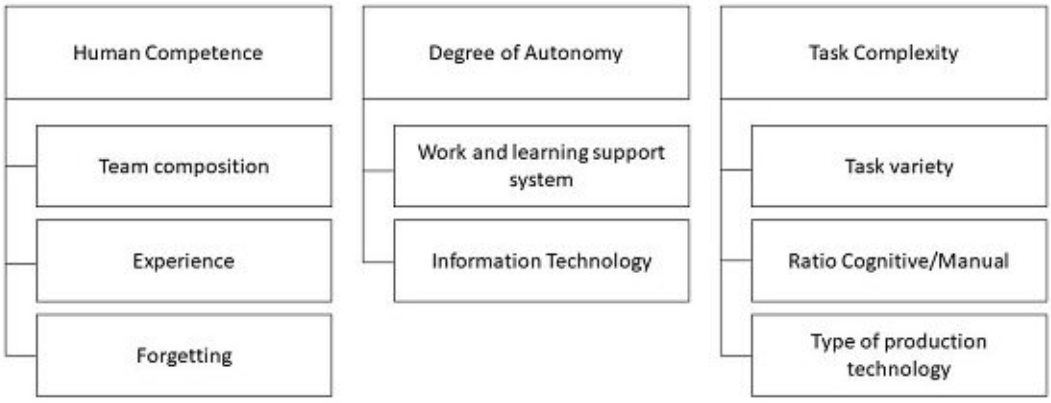

Figure 30: Classified factors

4.4 Learning Curve Development

To include all the previously researched categories and factors into a new model, the developed model is based on the multivariate learning curve elaborated in chapter 2.2.3. However, adaptations are necessary to ensure that including more factors into the model does not result in a smaller learning curve by default. The chosen multivariate learning curve model is used to determine factors out of a pre-defined learning curve by measuring the total amount of learning and distributing it on the relevant factors. The goal is to determine a learning curve by using the learning factors and calculating a total learning curve out of the individual factors. Formula 12 shows the proposed model, based on the multivariate learning curve model, that allows taking the factors elaborated in 4.2 into account and deriving a learning curve.

$$C_x = K \sum_{i=1}^{n} C_i x_i^{b_i}$$

Formula 12: Multivariate learning curve model

[198] Cf. Ansari, Erol, and Sihn (2018, p. 119f.).

To create a comprehensive model, it is useful to classify the previously used factors into more global categories defined in 4.3. The application of the classifiers results in a modified multivariate learning curve model.

$$C(x) = C_1 * (c_{Human} * x^{b_{Human}} + c_{System} * x^{b_{System}} + c_{Task} * x^{b_{Task}})$$

Formula 13: Proposed learning curve model

Formula 13 represents the developed learning curve model for our case. The coefficients have been adapted to represent the chosen classifiers: c_{Human} represents the human coefficient, c_{System} representing the system and c_{Task} the task coefficient. All of them will be evaluated by performing an AHP in the next steps. The learning rate slopes b_{Human}, b_{System} and b_{Task} will be evaluated as well during the analytic hierarchy process. C_1 represents the costs for the first produced unit, the same as in the log-linear learning curve.

4.5 Analytic Hierarchy Process

The analytic hierarchy process is explained in 4.1. In this chapter, the hierarchy is established and the calculations are described.

The hierarchy of the developed model is determined by the factors elaborated in 4.2 and the categories defined in 4.3. Figure 31 shows the selected hierarchy, the main criteria consisting of the human, system and task category. The sub-criteria contain the categorized factors that all have an impact on the learning curve.

The selected hierarchy is used for every application of the developed learning model. The optimization process to calculate the weighted factors needs to be performed for every new application as the relations and involves changing factors depending on the applications.

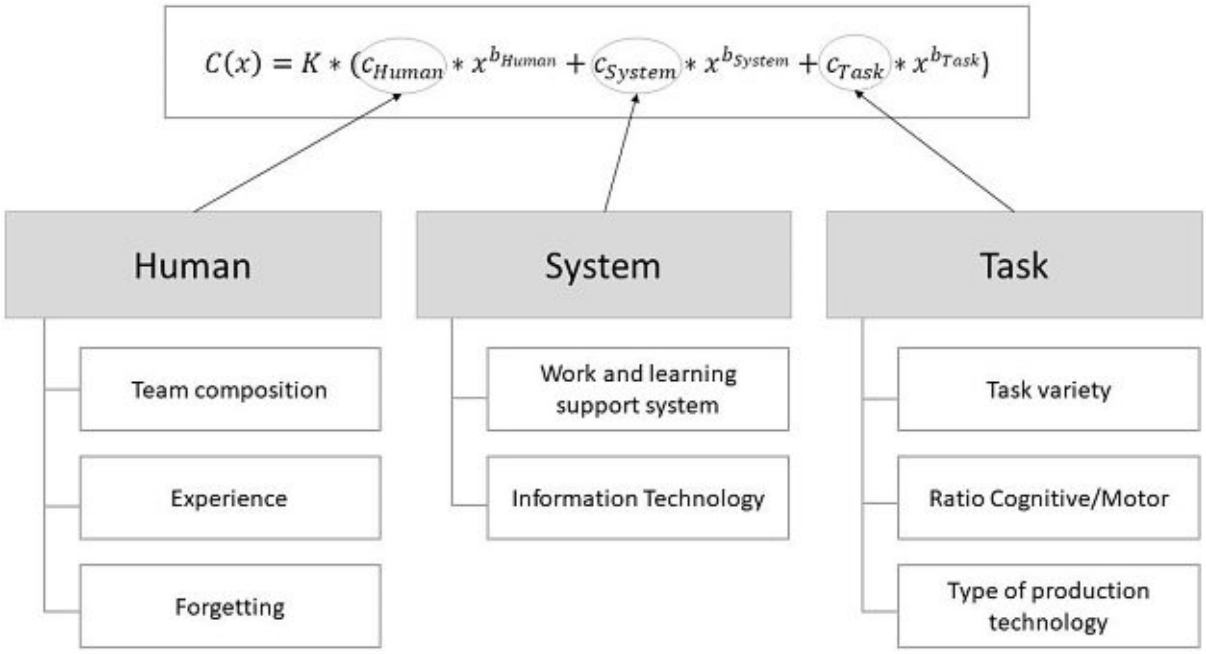

Figure 31: Hierarchy of the developed model

All elements of every level are being compared one to another, using a scale from 1 to 9, as shown in Figure 32. 1 means that both criteria represent the same importance, 3 represents the first criterion being slightly more important than the second one, 5 representing the first criterion being more important than the second one, 7 representing the first criterion being much more important than the second one and 9 representing the first criterion being extremely more important than the second one.[199]

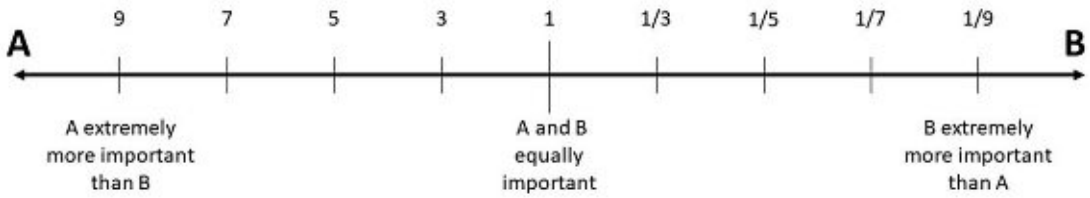

Figure 32: Pairwise comparison in AHP

These pairwise comparisons are done for every level of the hierarchy from lower to upper level. With the values of the pairwise comparison, it is possible to establish a comparison matrix for each criterion and level. Every element of the matrix represents a pairwise comparison. Logically, when comparing a criterion q with a criterion p, the comparison of p with q must provide the inverse value. The next step is the calculation

[199] Cf. Danner et al. (2011, pp. 371ff.).

of the relative weights of every criterion and sub-criterion for the overlying element. The weight of every element is represented by the principal right eigenvector.

$$CI = \frac{\lambda_{max} - n}{n - 1}, \qquad CR = \frac{CI}{RI}$$

Formula 14: Consistency index

By using Formula 14, the consistency ratio is being calculated. The random consistency index is used with fixed values for n=1 to 10. Due to the missing ability of the decision maker to precisely compare the criteria, it is necessary to check the consistency of the pairwise comparisons performed earlier. Slight deviations are accepted and a limit of 0.1 is defined for the consistency ratio.[200] [201]

The AHP application has the following steps:

- Step 1: Decomposition of the problem into a hierarchy of goal, criteria and sub-criteria. This step is fundamental as it establishes the relation between the factors.
- Step 2: Pairwise comparison of both criteria and sub criteria, by using the 1–9 scale. The pairwise comparison is based on either expert input, literature research or obvious facts.
- Step 3: Creation of the comparison matrix using the results obtained in Step 2.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, with\ a_{ij} = \frac{1}{a_{ji}}$$

- Step 4: Calculation of the normalised matrix and determination of the weights by dividing the matrix values by their column sum.

$$A_w = \begin{bmatrix} \frac{a_{11}}{\sum a_{i1}} & \cdots & \frac{a_{1n}}{\sum a_{in}} \\ \vdots & \ddots & \vdots \\ \frac{a_{n1}}{\sum a_{i1}} & \cdots & \frac{a_{nn}}{\sum a_{in}} \end{bmatrix}$$

- Step 5: Calculation of the weight values C_i by taking the mean value of the row sum of the normalised matrix A_W for every row.

$$C = \begin{bmatrix} C_1 \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} \frac{\frac{a_{11}}{\sum a_{i1}}}{n} + \cdots + \frac{\frac{a_{1n}}{\sum a_{in}}}{n} \\ \vdots \\ \frac{\frac{a_{n1}}{\sum a_{i1}}}{n} + \cdots + \frac{\frac{a_{nn}}{\sum a_{in}}}{n} \end{bmatrix}$$

- Step 6: Calculation of the x_i values by multiplying the comparison matrix with the vector containing the weight values C_i.

[200] Cf. Mühlbacher and Kaczynski (2013, pp. 120ff.).
[201] Cf. Bhushan and Rai (2004, pp. 12ff.).

$$A \times C = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \times \begin{bmatrix} C_1 \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

- Step 7: Calculation of λ_{max}, the eigenvalue of the pairwise comparison matrix.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{x_i}{c_i}$$

- Step 8: Calculation of the consistency ratio by using the consistency index CI as well as the random consistency index which is given for every n.

$$CI = \frac{\lambda_{max} - n}{n - 1} \; and \; CR = \frac{CI}{RI}$$

These steps need to be performed for every criterion and sub-criterion.[202]

4.6 Feedback Loop

A feedback loop is introduced as a last step of the model development to deal with deviations of the expected outcome and measured results. Especially in the early stage of the model application, a feedback process is important to ensure the correct application of the pairwise comparison of the AHP introduced in 4.5. After several applications of the developed learning model, a knowledge base should be established that supports the pairwise comparison of the influencing factors through similar applications. The feedback process is introduced below in Figure 33 showing its design.

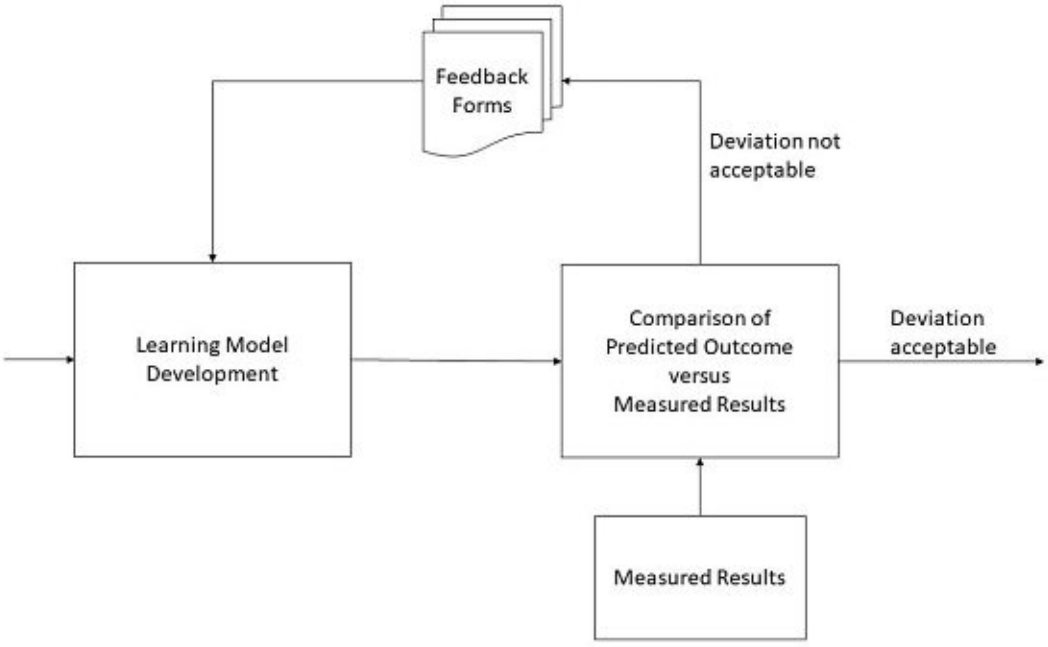

Figure 33: Feedback loop

[202] Cf. Sorooshian (2015, p. 2407f.).

The comparison of the predicted change along the learning curve and therefore the change in outcome versus the measured improvement time is evaluated. If the deviation is within acceptable limits, the pairwise comparison has been done correctly. If not, feedback forms should be filled out by the worker assessing how much influence the influencing factors had on the performed task. Based on these feedback forms, the pairwise comparison of the AHP will be adapted until the observed results are aligned with the predictions. A typical feedback form is presented in the application of the model development on a use case.

5 Model Application in a Maintenance Use Case

The usability and validity of the developed model is tested in a use case. A maintenance use case in a cyber-physical production environment is simulated. First of all, the learning rates for the factors are calculated, the factors are grouped and the AHP is applied. A small description of the used maintenance key performance indicators and an overview of their relationship towards the learning curve is presented. The model development is performed for a human-centred approach, a system-centred approach and a shared approach. As a final step, the influence of the learning curve on the overall equipment effectiveness is reviewed.

5.1 Learning Curve Optimization for Use Case

The considered use case is a maintenance activity in a smart factory. The simulated scenario consists of a technician performing a maintenance task: changing a component of a production machine. The following points elaborate on the actors in the scenario, namely the technician representing the human component, the system and the task itself.

5.1.1 Use Case Scenario

The presented use case helps to simulate an application of the developed learning model. The considered scenario represents a maintenance action in a smart factory.

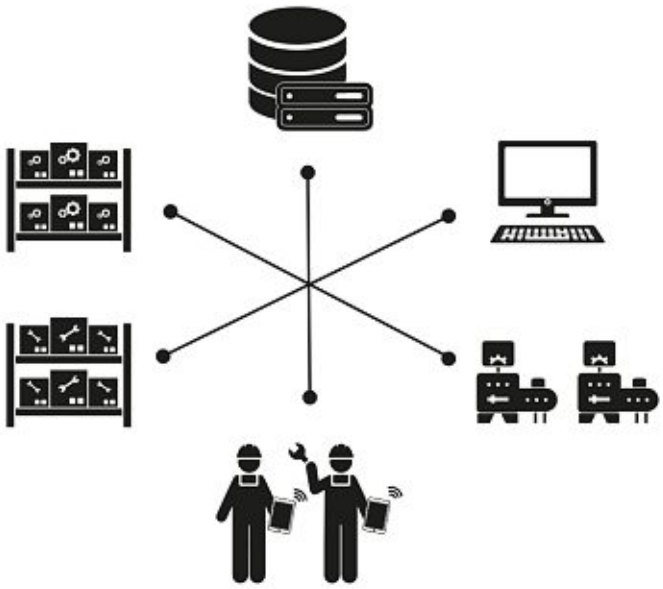

Figure 34: Maintenance use case scenario

Scenario: The considered scenario is a smart factory with several production machines. Condition monitoring of the production machines is performed by recording

energy consumption, temperatures, acceleration and vibration. The recorded data is transferred to the database and is analysed. When surpassing a defined threshold, the faulty component is identified and an alarm is raised. The maintenance management system schedules a replacement of the faulty component, requests the necessary parts from the stockroom, necessary tools from the toolroom and organizes the available maintenance technicians.

Actors: Main actors in the use case are the maintenance technicians who represent the human component. The system is represented by the smart factory and the maintenance management system. Its main purpose is the data analysis and the coordination of the maintenance process.

Interfaces: The interface between the human and the system component is the maintenance workers' tablet. Information is transmitted via the wireless network in the smart factory. The tablet enables the worker to access all necessary information required to efficiently perform the repair. All relevant info about the defect production machine is transferred to the worker such as maintenance history and location on the shopfloor. The necessary parts and tools are shown on the tablet and can be picked up from the stockroom. During the repair process, the tablet serves as a working assistance system, delivering repair instructions to the worker.

5.1.2 Hierarchy

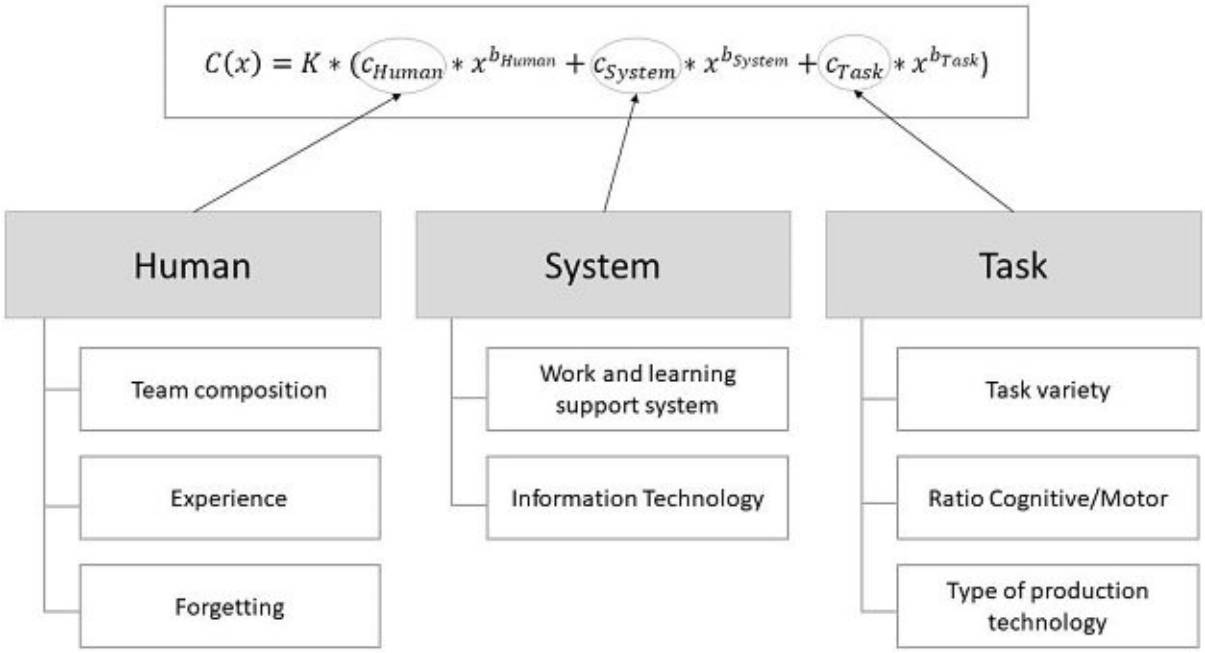

Figure 35: AHP hierarchy

The chosen hierarchy for our AHP is shown in Figure 35. The top level is our learning curve with the coefficients that need to be determined with the corresponding criteria being human competence, degree of autonomy and task complexity. The sub-criteria

for the respective criteria are the previously defined learning factors that were assigned according to their classification to one of the three coefficients.

5.1.3 Pairwise Comparison

As stated previously in chapter 5.1.2, the hierarchy has been established for the developed model and can be used for every suitable use case. The pairwise comparison, on the other hand, needs to be performed for every use case as it changes depending on the tasks performed, the available human competences and the degree of autonomy of the system.

As the results of the AHP are very sensitive towards false pairwise comparisons, it is important to base the decision on literature research and obvious facts of the analysed use case. Furthermore, a feedback control system is introduced in 4.6, delivering feedback from the comparison of the calculated and observed values in practice. This allows the user to adapt the pairwise comparison of the factors and achieve a more efficient model. To ensure that the pairwise comparison is consistent in itself, the consistency index is calculated as described in step 8 of 4.5.

Sub-criteria: human

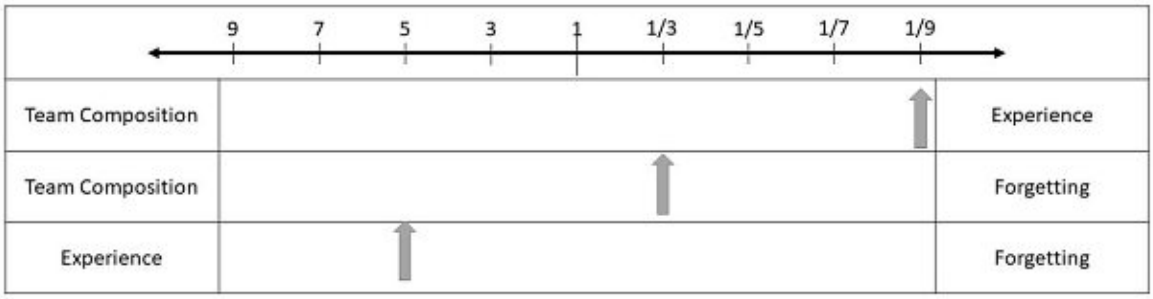

Figure 36: Pairwise comparison for human sub-criteria

For the human sub-criteria, the first pairwise comparison consists of comparing the importance of the team composition against the experience of the learner. Human experience is rated as extremely more important than the team composition. Learning depends on the actual experience level of the learner. With less experience, the learner is more dependent on external information and knowledge from others such as their team members.[203]

The comparison of team composition and forgetting is similar to the comparison of team composition and experience. Information and knowledge provided by team members is relevant in case of forgetting. As a conclusion, team composition is

[203] Cf. Argote et al. (2000, pp. 3ff.).

dependent on the occurrence of forgetting and needs to be rated slightly less important than forgetting.

The last comparison is experience versus forgetting. Experience is rated more important than forgetting due to the following reasons. The process of familiarity determines the characteristics of the learning curve and experience can associated with familiarity in a working environment.[204] Forgetting occurs soon after learning at an exponential rate, which leaves someone more experienced with a higher level of task knowledge compared to someone without prior experience.[205]

Sub-criteria: system

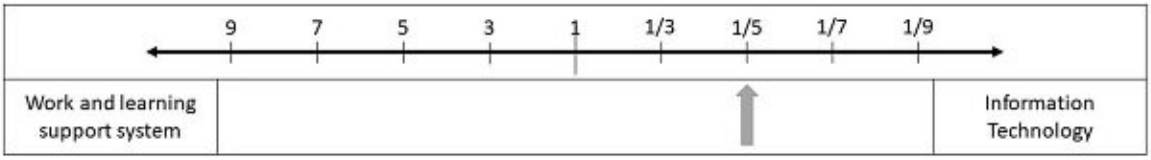

Figure 37: Pairwise comparison for system sub-criteria

Information technology contains application modules that are connected via information middleware to work assistance systems. Work assistance systems are therefore relying on the data provided by the overlying systems. Resource monitoring systems or tool management systems are examples of application modules providing the relevant data for work assistance systems.[206] Work and learning assistance systems in smart factories are dependent on the overlying information technology whereas information technology applications are able to deliver information to the user without work and learning assistance systems. Information Technology is therefore rated slightly more important than work and learning assistance systems.

Sub-criteria: task

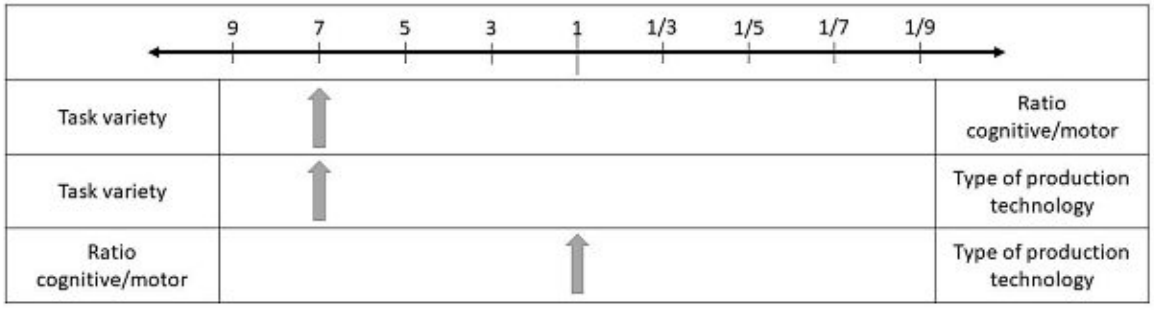

Figure 38: Pairwise comparison for task sub-criteria

[204] Cf. Yang et al. (2016, p. 375).
[205] Cf. Elliott et al. (2014, p. 20).
[206] Cf. Yoon et al. (2019, pp. 372ff.).

A pairwise comparison is performed for the sub-criteria of task variety and the ratio of cognitive versus motor tasks. Based on studies performed with patients having encountered brain damage such as caused by stroke, the effects of dual tasks vs. single tasks on the cognitive-motor behaviour were evaluated. Dual tasks favour the establishment of cognitive and motor skills.[207] Task variety is greater for multiple tasks than for a single task. Based on the above results, task variety is rated more important than the ratio of cognitive versus motor tasks.

Assigning a specialized task to a worker improves the productivity during the day whereas task variety improves productivity over a longer time.[208] Charles Perrow proposed a model to analyse organizational technology that classifies production technologies based on their task variability and task analysability.[209] Taking into account Perrow's model and the effects of task variety on productivity and therefore learning, task variety is rated more important than the used production technology.

The pairwise comparison of the type of production technology and ratio of cognitive versus motor tasks is based on the previous comparison with task variety being rated more important than both. The have a smaller impact on learning than task variety and can therefore be rated as equally important.

Main criteria

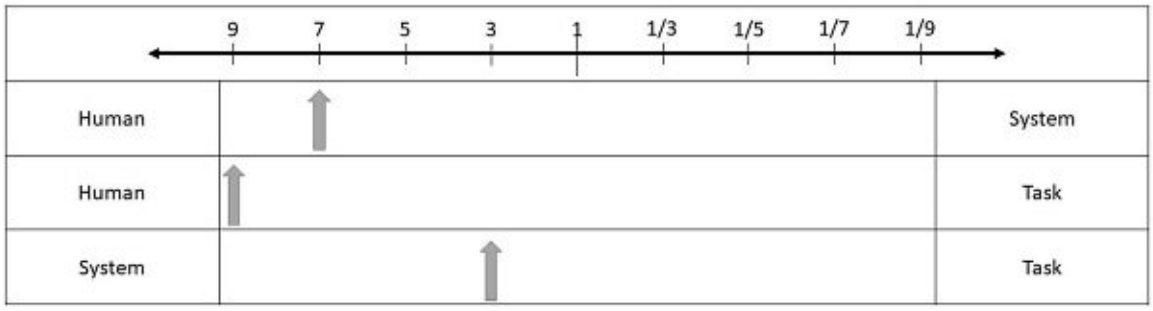

Figure 39: Pairwise comparison of the main criteria

To be consistent with previous research of Ansari et al. (2018), the focus is on a human-centred approach. This human-centred approach aims to convert todays smart factories into human self-learning factories[210] In 5.5.4, the human-centred approach is compared to a system-centred approach and an approach where human and system are equal in terms of decision making. To represent a human-centred approach, the human criterion is rated more important than the system and much more important

[207] Cf. Patel and Bhatt (2014, p. 355).
[208] Cf. Staats and Gino (2011, p. 20).
[209] Cf. Jaffee (2001, p. 188).
[210] Ansari, Hold, Mayrhofer et al. (2018, p. 62).

than the task criterion. As the use case is simulating a maintenance activity in a smart factory, the system is rated slightly more important than the task criterion.

The usage of the analytical hierarchy process requires the pairwise comparison to be displayed in a matrix format. The following matrices are obtained for the sub-criteria:

$$A_{Human} = \begin{bmatrix} 1 & \frac{1}{9} & \frac{1}{3} \\ 9 & 1 & 5 \\ 3 & \frac{1}{5} & 1 \end{bmatrix} \qquad A_{System} = \begin{bmatrix} 1 & \frac{1}{5} \\ 5 & 1 \end{bmatrix} \qquad A_{Task} = \begin{bmatrix} 1 & 7 & 7 \\ \frac{1}{7} & 1 & 1 \\ \frac{1}{7} & 1 & 1 \end{bmatrix}$$

The pairwise comparison of the main criteria results in the following matrix:

$$A_{Model} = \begin{bmatrix} 1 & 7 & 9 \\ \frac{1}{7} & 1 & 3 \\ \frac{1}{9} & \frac{1}{3} & 1 \end{bmatrix}$$

5.1.4 Normalised Matrix

The pairwise comparison matrices are normalized in order to obtain a common scale to enable aggregation of numerical and comparable criteria.[211] The performed calculation is described in detail in step 3 of 4.5.

$$AW_{Human} = \begin{bmatrix} 0.08 & 0.08 & 0.05 \\ 0.69 & 0.76 & 0.79 \\ 0.23 & 0.15 & 0.16 \end{bmatrix} AW_{System} = \begin{bmatrix} 0.25 & 0.25 \\ 0.75 & 0.75 \end{bmatrix} AW_{Task} = \begin{bmatrix} 0.78 & 0.78 & 0.78 \\ 0.11 & 0.11 & 0.11 \\ 0.11 & 0.11 & 0.11 \end{bmatrix}$$

$$AW_{Model} = \begin{bmatrix} 0.8 & 0.84 & 0.69 \\ 0.11 & 0.12 & 0.23 \\ 0.09 & 0.04 & 0.08 \end{bmatrix}$$

5.1.5 Weight Vectors

Step 4 in Chapter 4.5 is about the calculation of the weighted vectors. The weighted vectors contain the priorities of the selected criteria.

$$C_{Human} = \begin{bmatrix} 0.07 \\ 0.75 \\ 0.18 \end{bmatrix} \qquad C_{System} = \begin{bmatrix} 0.25 \\ 0.75 \end{bmatrix} \qquad C_{Task} = \begin{bmatrix} 0.78 \\ 0.11 \\ 0.11 \end{bmatrix}$$

$$C_{Model} = \begin{bmatrix} 0.78 \\ 0.15 \\ 0.07 \end{bmatrix}$$

[211] Cf. Vafaei et al. (2018, p. 43).

5.1.6 Consistency Index and Consistency Ratio

An essential item of the analytical hierarchy process is the consistency index that allows to determine if the pairwise comparisons of every criterion and sub-criterion are consistent within each other. Step 5 to 7 in Chapter 4.5 elaborate on the performed calculations. The eigenvector is calculated out of the weight vector and the normalised matrix.

$$\lambda_{Human} = \begin{bmatrix} 3.01 \\ 3.06 \\ 3.02 \end{bmatrix} \qquad \lambda_{System} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \qquad \lambda_{Task} = \begin{bmatrix} 3 \\ 3 \\ 3 \end{bmatrix}$$

$$\lambda_{Model} = \begin{bmatrix} 3.19 \\ 3.04 \\ 3.01 \end{bmatrix}$$

The eigenvalue is derived for every eigenvector.

$$\lambda_{\max\ Human} = 3.03 \qquad \lambda_{\max\ System} = 2 \qquad \lambda_{\max\ Task} = 3$$

$$\lambda_{\max\ Model} = 3.08$$

The consistency index is calculated by applying the formulas contained in step 6 of Chapter 4.5.

$$CI_H = 0.015, \qquad CR_H = 0.025 < 0.1$$
$$CI_S = CR_S = \ 0 < 0.1$$
$$CI_T = CR_T = \ 0 < 0.1$$
$$CI_M = 0.041, \qquad CR_M = 0.071 < 0.1$$

The evaluated consistency ratios are all smaller than 0.1, the pairwise comparisons are consistent. The weights for the evaluated criteria can be accepted.

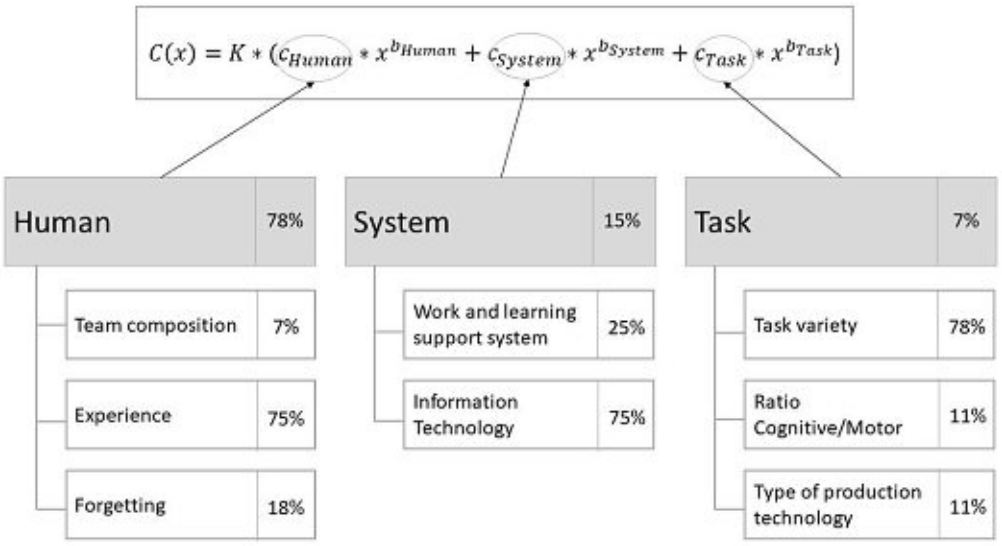

Figure 40: AHP hierarchy including results

Figure 40 shows the values of the criteria and sub-criteria. To determine the learning rates of our developed model, the mean learning slopes of every factor elaborated in 2.3 are used. An overview is available in Table 8.

Table 8: Learning rates used in the developed model

Factor	Learning slope range	Mean learning slope
Team composition	[−0.016; −0.034]	−0.025
Experience	[−0.007; −0.034]	−0.0205
Forgetting	[0.017; 0.017]	0.017
Work and learning assistance system	[−0.122; −0.155]	−0.1385
Information technology	[−0.16; −0.16]	−0.16
Task variety	[−0.14; −0.4]	−0.27
Ratio cognitive/motor	[−0.152; −0.514]	−0.333
Type of production technology	[−0.219; −0.427]	−0.323

By applying the factor weights calculated in the AHP progress as well as the mean learning slopes from the researched factors, we can build our own multi-factor learning model with a focus on human learning. Formula 15 shows the values calculated for the learning model with a focus on human learning.

$$C(x) = C_1 * (0.78 * x^{-0.02} + 0.15 * x^{-0,155} + 0.07 * x^{-0.283})$$

Formula 15: Human-centred learning model

5.1.7 Feedback Form

Figure 41 presents a draft feedback form that could be used to adapt the pairwise comparison explained in 5.1.3 and correct possible wrong comparisons due to a lack of expert knowledge.

Feedback Form

Personal Information

Name
Date: Workorder:

Explanation

Please fill out the Feedback Form regarding your experience during the task execution.
Please rate below aspects present during task execution.

Human Factors

	Helpful	Neutral	Unnecessary
Team Member	☐	☐	☐
Own Experience	☐	☐	☐
Own ability to remember necessary steps	☐	☐	☐

System Factors

	Helpful	Neutral	Unnecessary
Assistance Device	☐	☐	☐
System Support	☐	☐	☐

Task Factors

	Helpful	Neutral	Unnecessary
Variety of the task	☐	☐	☐
Amount of cognitive work involved	☐	☐	☐
Amount if assembly work	☐	☐	☐

Figure 41: Feedback form draft

Based on the given answers of the learner, the pairwise comparison can be adjusted. The answers indicate the direction in which the pairwise comparison needs to be adjusted. Preferably, multiple feedback forms are collected to avoid that the pairwise comparison is adjusted based on a single learner experience. This feedback process should be performed as long as the observed values differ from the expected values.

5.2 System-Centred and Shared Approach

Opposite to the human-centred approach discussed in 5.1, this chapter develops a system-centred as well as a shared approach for learning in cyber-physical-social production systems. Ansari, Hold and Sihn (2018) defined a vector of competence to determine the dominance of human/CPPS in decision making.[212] To research the differences of the approaches, this chapter develops a model for a system-centred approach and an approach with equal decision taking.

The pairwise comparison of the sub-criteria remains unchanged for the approaches. It is specific for the considered use case elaborated in 5.1.1. The matrices are represented below.

[212] Cf. Ansari, Hold, and Sihn (2018, p. 2).

$$A_{Human} = \begin{bmatrix} 1 & \frac{1}{9} & \frac{1}{3} \\ 9 & 1 & 5 \\ 3 & \frac{1}{5} & 1 \end{bmatrix} \qquad A_{System} = \begin{bmatrix} 1 & \frac{1}{5} \\ 5 & 1 \end{bmatrix} \qquad A_{Task} = \begin{bmatrix} 1 & 7 & 7 \\ \frac{1}{7} & 1 & 1 \\ \frac{1}{7} & 1 & 1 \end{bmatrix}$$

For both the system-centred and shared approach, the main criteria need to be re-evaluated as shown in the following subchapters.

5.2.1 System-Centred Approach

CPPS with a high degree of autonomy allow semi-automatic decision support or standard decision-making support by CPPS.[213] The high degree of autonomy is represented in the model development by an updated pairwise comparison. The calculation of the weights is shown below for the main criteria, whereas the weights of the sub criteria remain unchanged.

$$A_{Model} = \begin{bmatrix} 1 & \frac{1}{7} & 3 \\ 7 & 1 & 9 \\ \frac{1}{3} & \frac{1}{9} & 1 \end{bmatrix}$$

$$AW_{Model} = \begin{bmatrix} 0.12 & 0.11 & 0.23 \\ 0.84 & 0.80 & 0.69 \\ 0.04 & 0.09 & 0.08 \end{bmatrix}$$

$$C_{Model} = \begin{bmatrix} 0.15 \\ 0.78 \\ 0.07 \end{bmatrix}$$

$$\lambda_{Model} = \begin{bmatrix} 3.04 \\ 3.19 \\ 3.01 \end{bmatrix}$$

$$\lambda_{\max Model} = 3.08$$

$$CI_{Model} = 0.041, \qquad CR_{Model} = 0.071 < 0.1$$

The system-centred learning model with the calculated values from above is displayed in Formula 16.

$$C(x) = C_1 * (0.15 * x^{-0.02} + 0.78 * x^{-0,155} + 0.07 * x^{-0.283})$$

Formula 16: System-centred learning model

[213] Cf. Ansari, Hold, and Sihn (2018, p. 2).

5.2.2 Shared Approach

The competence level of the human worker and the degree of autonomy of the production system define how decision making is performed in CPPS.[214] Prerequisites for shared decision making are the matching level of competence of the human worker and degree of autonomy of the system. If these conditions are fulfilled, a shared decision making is possible. The calculation below determines the weights of the main criteria. The weights of the sub-criteria remain unchanged as they are specific to the considered use case.

$$A_{Model} = \begin{bmatrix} 1 & 1 & 5 \\ 1 & 1 & 5 \\ \frac{1}{5} & \frac{1}{5} & 1 \end{bmatrix}$$

$$AW_{Model} = \begin{bmatrix} 0.455 & 0.455 & 0.455 \\ 0.455 & 0.455 & 0.455 \\ 0.090 & 0.090 & 0.090 \end{bmatrix}$$

$$C_{Model} = \begin{bmatrix} 0.455 \\ 0.455 \\ 0.090 \end{bmatrix}$$

$$\lambda_{Model} = \begin{bmatrix} 3.00 \\ 3.00 \\ 3.00 \end{bmatrix}$$

$$\lambda_{\max Model} = 3.00$$

$$CI_{Model} = CR_{Model} = 0.00 < 0.1$$

The shared approach with the calculated values from above is displayed in Formula 17.

$$C(x) = C_1 * (0.455 * x^{-0.02} + 0.455 * x^{-0,155} + 0.090 * x^{-0.283})$$

Formula 17: Human and system shared approach model

5.3 Influence of the Factors towards the Maintenance KPIs

EN13306 defines maintenance management as all activities of the management that determine the maintenance requirements, objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control and the improvement of maintenance activities and economics.[215] To support management decisions, supporting information is essential. For this purpose,

[214] Cf. Ansari, Hold, and Sihn (2018, p. 2).
[215] Norm DIN EN 13306, p. 9.

maintenance key performance indicators are introduced and the KPIs relevant for the use case presented in 5.1.1 are displayed in the next subchapter.

5.3.1 Maintenance KPIs

The discussed maintenance process of the presented use case is displayed in Figure 42. The actions of the main actors are represented as well as the state of the production machine and the key performance indicators. As soon as the production machine stops running, the repair process is initiated. The response time is determined by the time that is necessary to prepare the repair including commuting, coordination and procurement of parts and tools. Repair time can be split into the actual working time to exchange the component, the time to test whether the repair was successful and the time to start up the machine. A performance indicator to measure the repair time is the mean time to repair, shown in Formula 19.

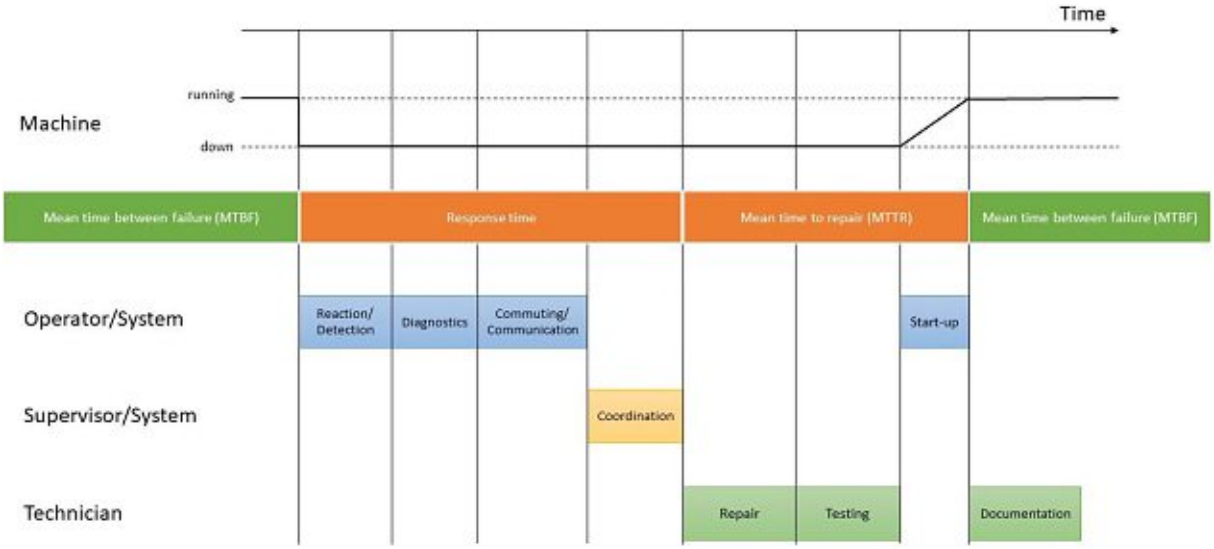

Figure 42: Maintenance KPIs

The overall equipment effectiveness reflects the equipment efficiency while the equipment is running. It is the most important indicator as it allows the operator to accurately analyse productivity losses.[216]

$$OEE = asset\ availability \times performance\ efficiency \times quality\ ratio$$

Formula 18: Overall equipment effectiveness

As mean time to repair we define the average breakdown time per repair.

[216] Cf. Dal et al. (2000, pp. 1488ff.).

$$MTTR = \frac{breakdown\ time\ total}{number\ of\ breakdowns}$$

Formula 19: Mean time to repair

Mean time between repair is the average time between repairs.

$$MTBR = \frac{time\ between\ repairs}{number\ of\ breakdowns}$$

Formula 20: Mean time between repairs

The average running time of an asset between breakdowns is the mean time between failures.

$$MTBF = \frac{MTBR + MTBF}{number\ of\ breakdowns}$$

Formula 21: Mean time between failures

5.3.2 Relationship of Learning Factors and Maintenance KPIs

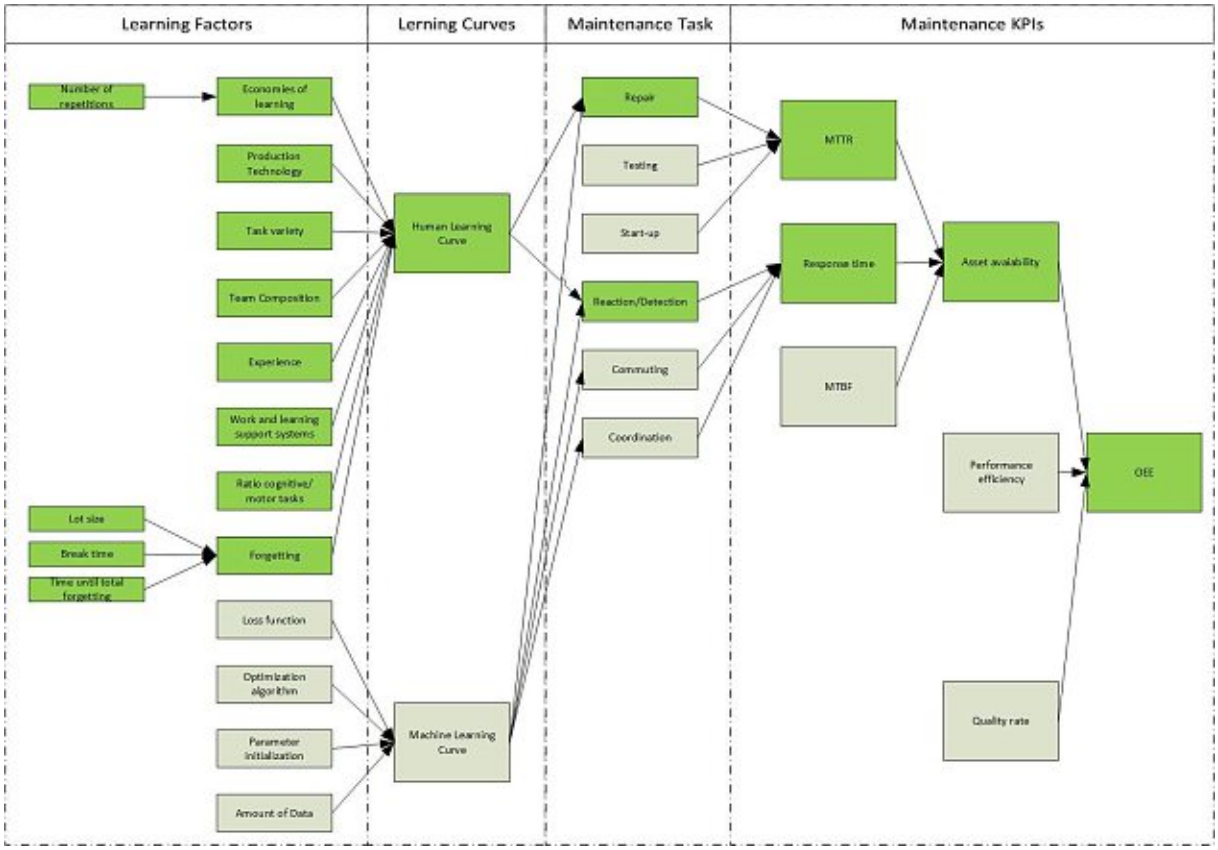

Figure 43: Relations in the developed model

Figure 43 shows the relations between the influencing factors, the learning curves and the maintenance KPIs. Starting on the left side, the factors influencing the human learning curve and the machine learning curve are displayed as well as their underlying

components. These factors directly influence the learning curves. The number of repetitions determines the improvement compared to the first task execution. These improvements are happening during certain steps when performing maintenance tasks. The execution time of the maintenance tasks directly influences the maintenance KPIs as shown in Figure 42.

A human-centred learning scenario is researched. Therefore, the model is restricted to the factors which influence the human learning curve. In Figure 43, these are marked in green, as well as the other variables considered in the developed model. The implementation of the model replicates the relations shown above with the values calculated in the previous chapters.

As shown in Figure 44, the human learning curve directly affects the repair time and the failure detection time as the worker knows the steps necessary to repair the machine after gaining experience and the root cause of the failure is found easier with a larger knowledge base of possible failures.

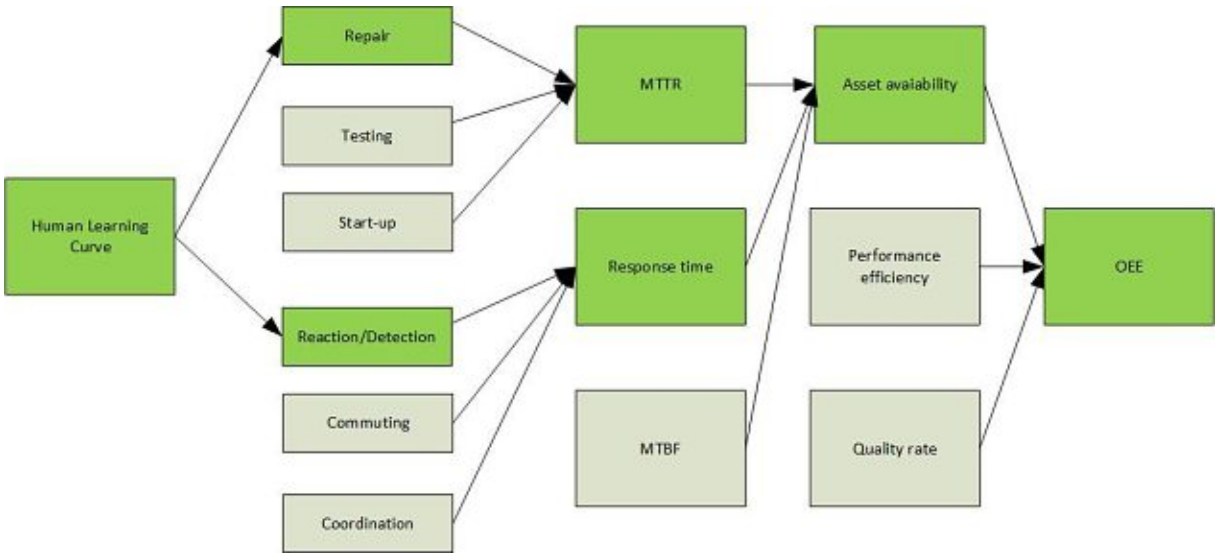

Figure 44: Effects of the learning curve on maintenance KPIs

The following formula describes the relation between the learning curve and the overall equipment effectiveness, the key performance indicator we are the most interested in. It reflects the changes of the overall equipment effectiveness due to a change in the output of the learning curve after a certain number of repetitions.

$$\Delta OEE = -\frac{1}{3} * \left(\Delta LC * MTTR_{repair} + \Delta LC * Response\ time_{Detection}\right)$$

Formula 22: Relationship of the OEE and learning curve

The following values were chosen for the composition of the mean time to repair.

Table 9: MTTR composition

MTTR	Percentage
Repair	50%
Testing	35%
Start-up	15%

The same way the composition of the response time was evaluated.

Table 10: Response time composition

Response time	Percentage
Reaction/Detection	60%
Commuting	20%
Coordination	20%

With the values from Table 9 and Table 10, Formula 22 has the following form.

$$\Delta OEE = -\frac{1}{3} * (\Delta LC * 0.5 + \Delta LC * 0.6)$$

Formula 23: Change in overall equipment effectiveness for a maintenance task

The change in overall equipment effectiveness is directly dependent on the improvement along the learning curve that results in a change of the output. The improvement depends on the form of the learning curve itself and the number of repetitions of the performed task, which determines where the learning curve is evaluated.

5.4 Simulation Dashboard

For an efficient application of the developed model in a real case scenario, a simulation dashboard has been developed. The dashboard visualizes the learning influence for the use case presented in 5.1.1 starting at the lowest level, the researched influencing factors defined in 2.3 up to the maintenance KPIs presented in 5.3.1. The dashboard was built and programmed in Microsoft Excel using the Visual Basic Editor. The design is shown in Figure 45. The first column on the left side of the dashboard represents the influencing factors, followed by the composition of the performed maintenance in subtasks. Maintenance KPIs are represented in the next column with the overall equipment effectiveness being displayed in the last column.

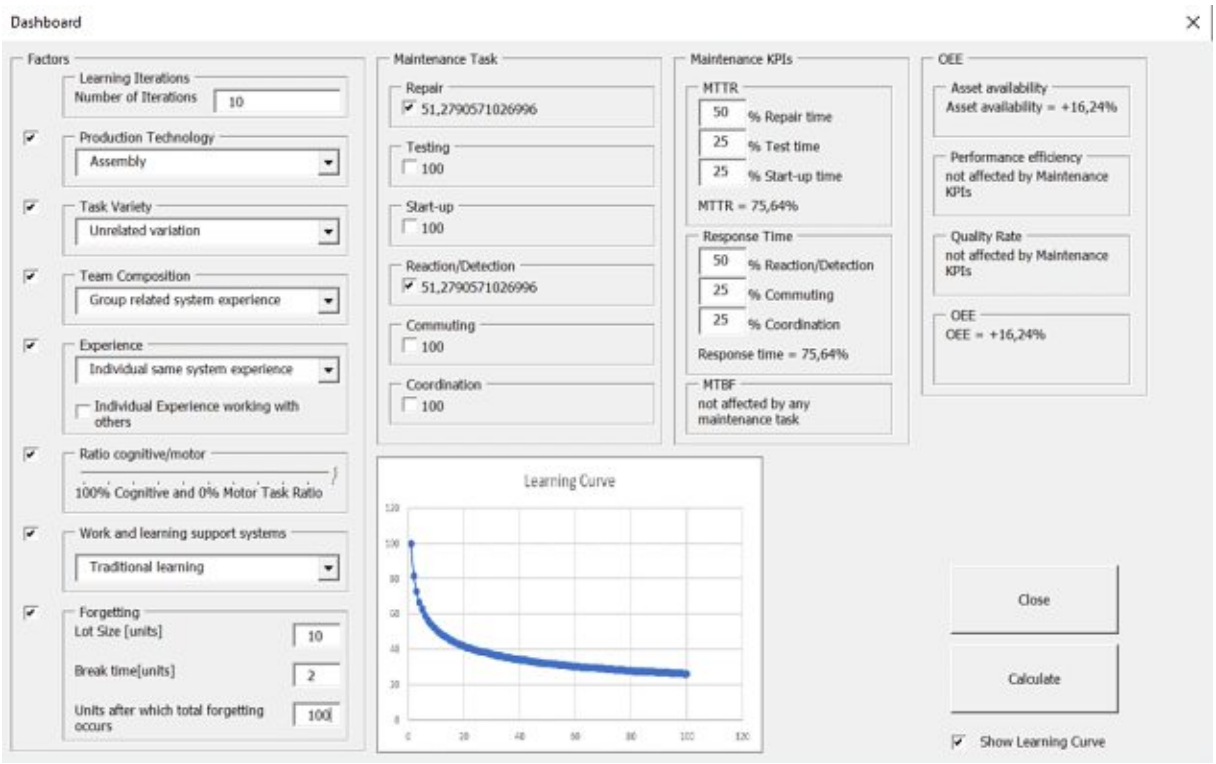

Figure 45: Dashboard

Figure 46 shows the section dealing with the **influencing factors** and allowing the user to select the factors that are relevant for his specific case.

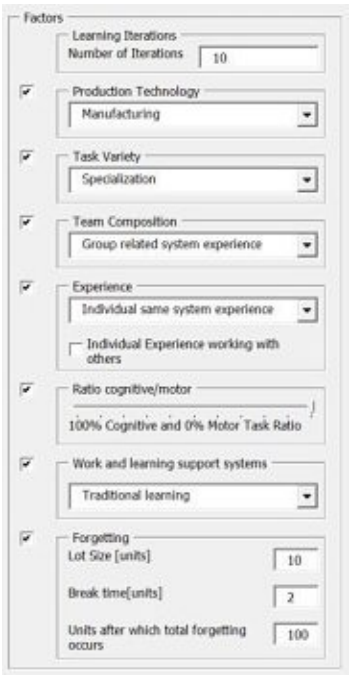

Figure 46: Factors section

Factors can be selected or deselected through the checkmark positioned in front of every factor. Possible choices for the factors are the researched options for the individual factors, evaluated in 4.2 with their regarding values. Factors that allow an

intermix of the researched options can be displayed using a slider and are calculated through interpolation using the known values evaluated in 4.2. In Figure 46 this has been done for the ratio of cognitive versus motor activities in a task. Other factors such as forgetting require the input of multiple parameters, achieved through the addition of input fields. As mentioned in 4.2, the number of iterations is essential to determine the achieved change along the learning curve. It determines the position where the learning curve is evaluated and is therefore mandatory on the dashboard and cannot be deselected.

The second section of the dashboard deals with the analysed **maintenance task** elaborated in 5.1.1. Figure 47 shows the task section before and after calculation of the learning curve. It lists all the subtasks of the maintenance task elaborated in Figure 42. The checkboxes depict the relationship between the learning curve and the affected subtasks. The configuration shown below represents the relationship displayed between the two first columns of Figure 44. After the calculation, the necessary execution time is shown for every subtask in percent of the initial completion time.

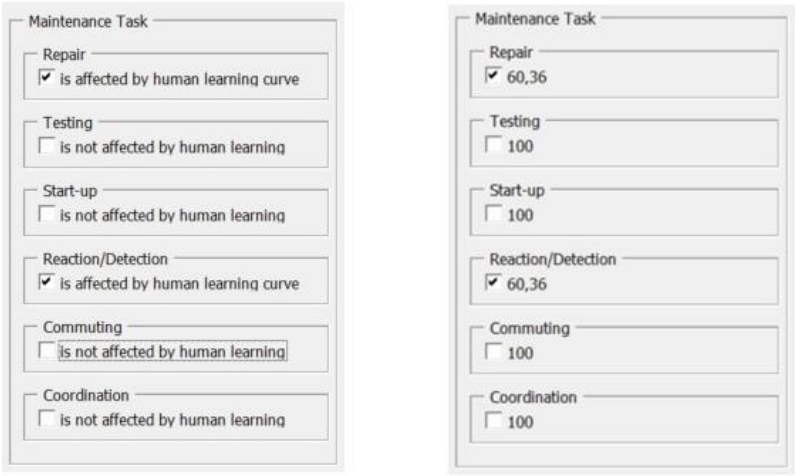

Figure 47: Task section before and after calculation

The calculation of the improvement for the subtasks is followed by the calculation of the **maintenance KPIs.** The maintenance KPIs mentioned in Figure 42 are represented in that section. Their composition can be adjusted based on the values from Table 9 and Table 10. The achieved values of the KPIs are presented after calculation of the learning curve.

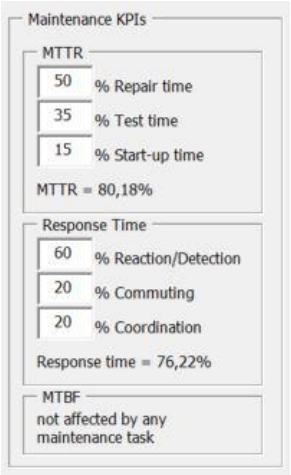

Figure 48: Maintenance KPIs section

As a last step the change of the overall equipment effectiveness is presented in the **OEE** section, which represents the most important indicator for a production process, is calculated. As displayed in Figure 49, the final result of the OEE improvement is displayed. The relationship between the maintenance KPIs elaborated in the previous point.

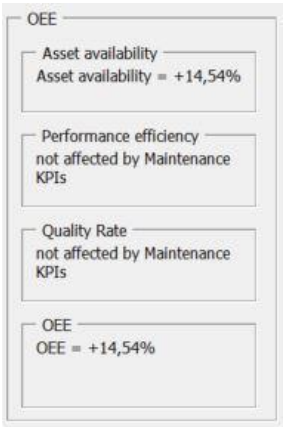

Figure 49: Overall Equipment Effectiveness section

The purpose of this tool is to show the possible improvements triggered by changes in how the tasks are composed and how the employees are trained. For the usage in an industrial environment, simulating a real production process, it would be necessary to adapt the initial learning rates for the specific process. Furthermore, the ratios of the tasks during a maintenance task should be defined in collaboration with the maintenance engineer and the plant operator. As shown in Figure 45, such a dashboard should be customizable and offer the possibility to adapt the structure of the process. In the investigated case this is achieved by the customizability of the composition of the KPIs. Such a tool can easily be used when planning a new process and scheduling the necessary trainings or evaluating the necessary assistance systems to achieve a certain improvement compared to a previous production process.

5.5 Results

This chapter presents the results achieved with the developed models applied to the use case presented in 5.1.1. The results of the human-centred learning model are analysed as well as its improvements along the learning curve. Both the system-centred and shared approach are evaluated and compared against each other. The last point of this chapter is the effect of the improvement along the learning curve and its effect on the KPIs.

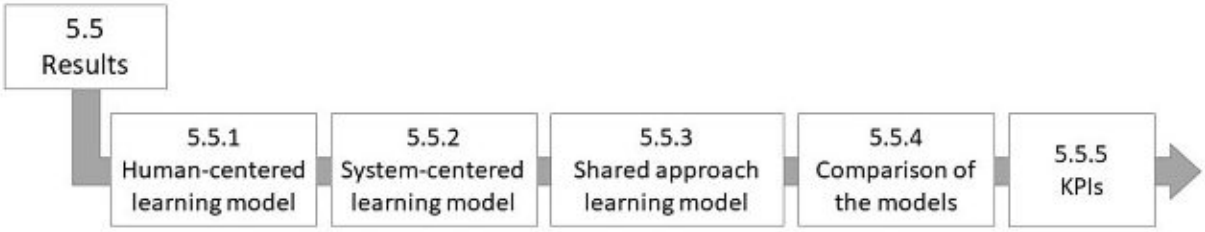

Figure 50: Structure of Chapter 5.5

5.5.1 Human-Centred Learning Model

The human-centred learning curve has been developed for the maintenance use case. The simulated learning curve is presented in Formula 24. With the model being developed as human-centred, the human parameter represents the most important value. The second highest parameter is the system parameter, whereas the task parameter is represented by the lowest value.

$$C(x) = C_1 * (0.78 * x^{-0.02} + 0.15 * x^{-0,155} + 0.07 * x^{-0.283})$$

Formula 24: Human-centred learning model

Figure 51 shows the plotted human-centred learning curve. An initial value of 100 has been selected for C_1.

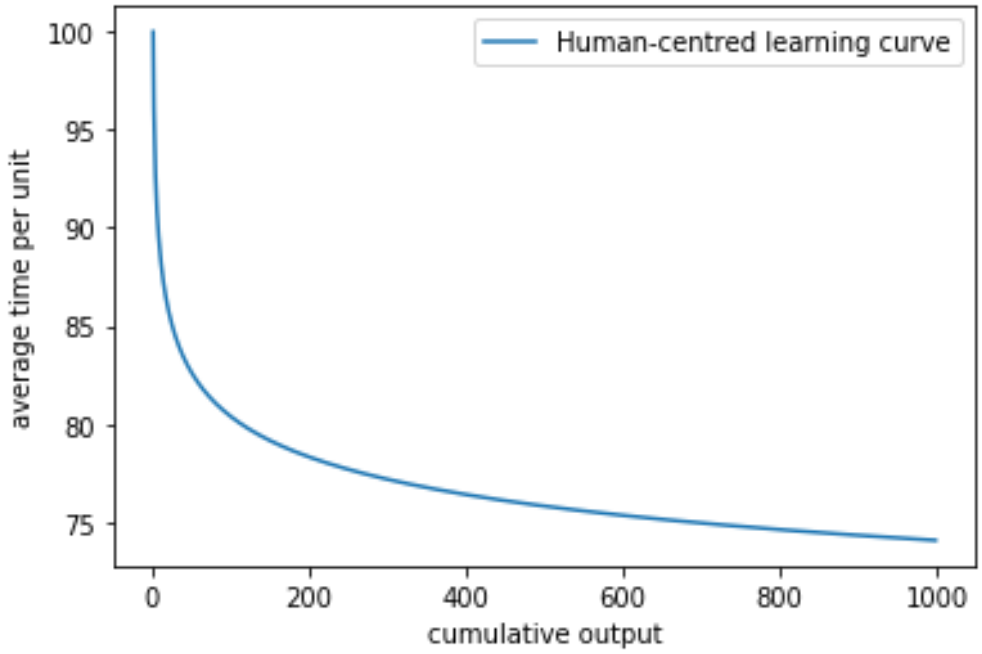

Figure 51: Human-centred learning curve

To evaluate when the learning curve reaches a stationary state, the derivative of Formula 24 is calculated.

$$\frac{\partial}{\partial x} C_1 * (0.78 * x^{-0.02} + 0.15 * x^{-0,155} + 0.07 * x^{-0.283})$$

$$= \frac{C_1 * (0.78 * (-0.02) * x^{-0.02} + 0.15 * (-0.155) * x^{-0,155} + 0.07 * (-0.283) * x^{-0.283}}{x}$$

$$= \frac{C_1 * (-0.016 * x^{-0.02} - 0.023 * x^{-0,155} - 0.02 * x^{-0.283})}{x}$$

Formula 25: Human-centred learning model derivative

The derivative plotted over the cumulative output represents the change of the slope gradient of the learning curve. The points marked in Figure 52 display the curve gradient for every 20 task repetitions.

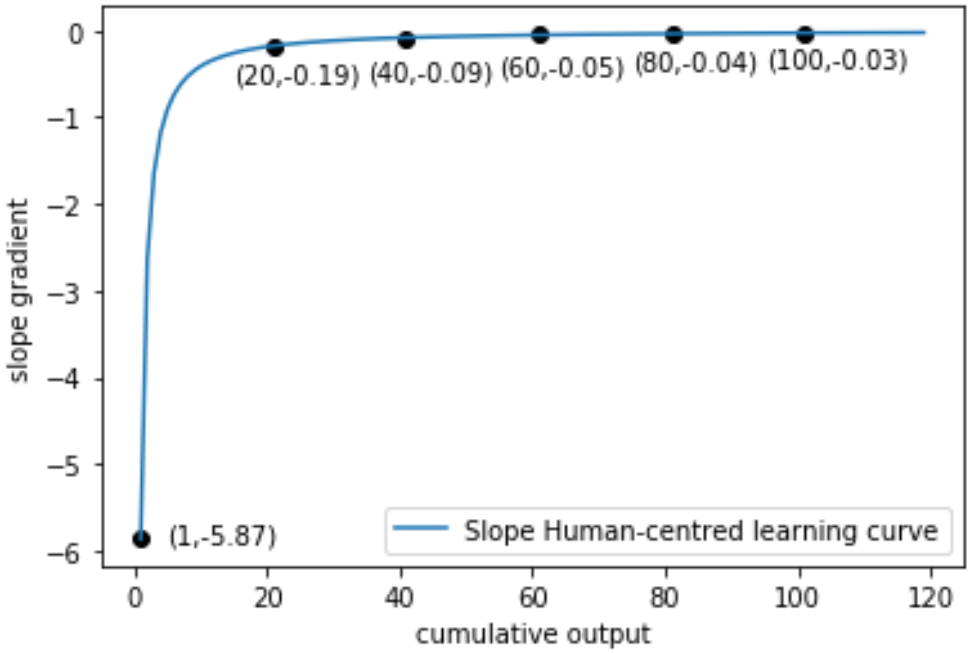

Figure 52: Human-centred learning curve slope

Analysing the slope shows that after 60 iterations, the slope increases only by 0.01 for 20 iterations. For the first 20 iterations, an increase of 5.68 is calculated.

5.5.2 System-Centred Learning Model

In addition to the human-centred learning curve, the system-centred learning curve has been developed as well.

$$C(x) = C_1 * (0.15 * x^{-0.02} + 0.78 * x^{-0,155} + 0.07 * x^{-0.283})$$

Formula 26: System-centred learning model

Figure 53 represents the system-centred learning curve. After 100 repetitions, the necessary time to perform the evaluated task is consists of 54% of the initial value and 49% after 200 repetitions.

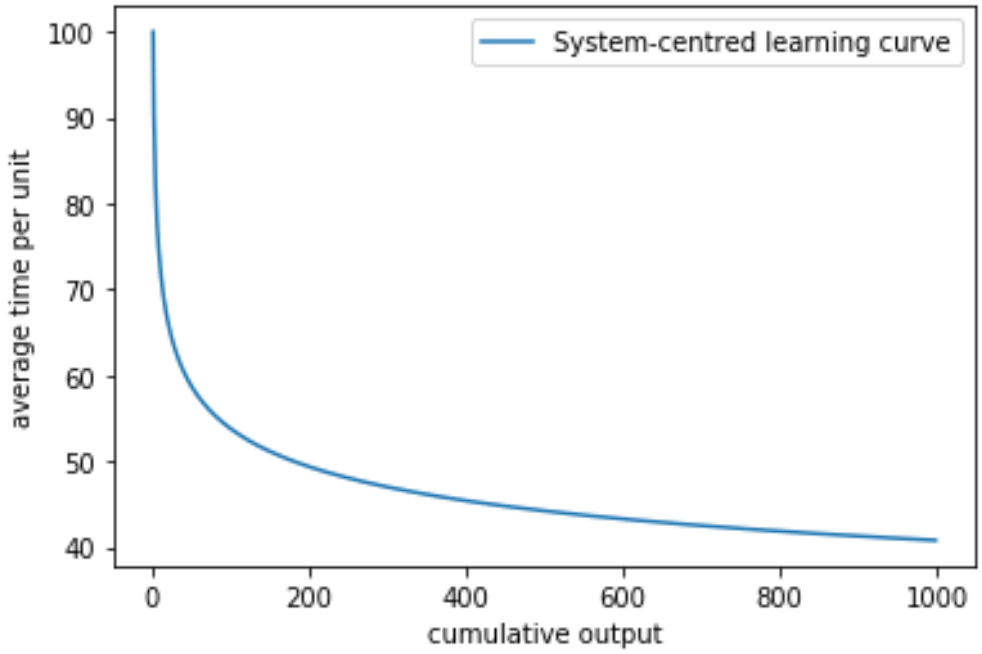

Figure 53: System-centred learning curve

Similar to the evaluation of the gradient of the human-centred learning curve performed in 5.5.1, the derivative of Formula 26 is calculated:

$$\frac{\partial}{\partial x} C_1 * (0.15 * x^{-0.02} + 0.78 * x^{-0,155} + 0.07 * x^{-0.283})$$

$$= \frac{C_1 * (-0.003 * x^{-0.02} - 0.1209 * x^{-0,155} - 0.02 * x^{-0.283})}{x}$$

Formula 27: System-centred learning model derivative

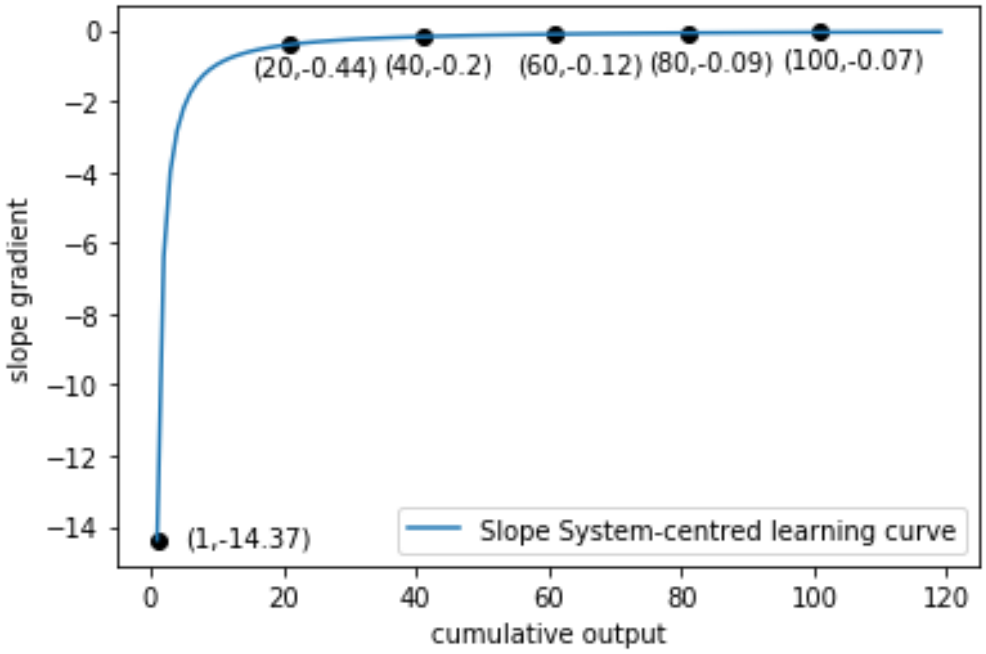

Figure 54: System-centred learning curve slope

The initial slope of the learning curve when performing the first repetition is −14.37. After 20 repetitions it raised to −0.44, which represents an increase of 13.93. After 80 repetitions, the slope is rising by 0.02 for 20 repetitions.

5.5.3 Shared Approach Learning Model

As an addition to the human-centred and system-centred model, the shared model is evaluated. Decision making ability is distributed equally between humans and the system. Formula 28 displays the shared approach model. The system and the human parameter have the same value as defined per decision of the shared model.

$$C(x) = C_1 * (0.455 * x^{-0.02} + 0.455 * x^{-0,155} + 0.090 * x^{-0.283})$$

Formula 28: Shared approach model

An analysis of the plotted learning curve presented in Figure 55 delivers the following improvements: 66% of the time is needed to perform the 100th task compared to the first task performed. After 200 repetitions, a further reduction to 63% of the necessary performance time is achieved.

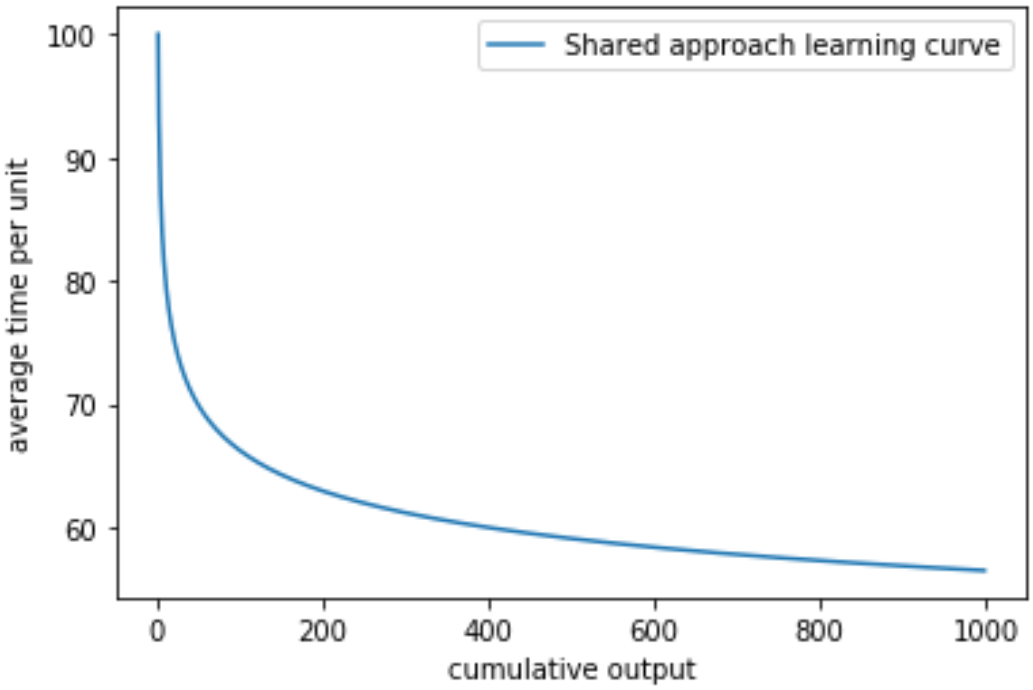

Figure 55: Shared approach learning curve

An analysis of the plotted learning curve presented in Figure 55 delivers the following improvements: 66% of the time is needed to perform the 100th task compared to the first task performed. After 200 repetitions, a further reduction to 63% of the necessary performance time is achieved.

$$\frac{\partial}{\partial x} C_1 * (0.455 * x^{-0.02} + 0.455 * x^{-0,155} + 0.09 * x^{-0.283})$$

$$= \frac{C_1 * (-0.009 * x^{-0.02} - 0.071 * x^{-0,155} - 0.025 * x^{-0.283})}{x}$$

Formula 29: Shared approach model derivative

The derivative of the shared approach model is represented by Formula 29. Plotted over the cumulative output with indication of the slope values at defined number of iterations allows to analyse the evaluation of the slope gradient.

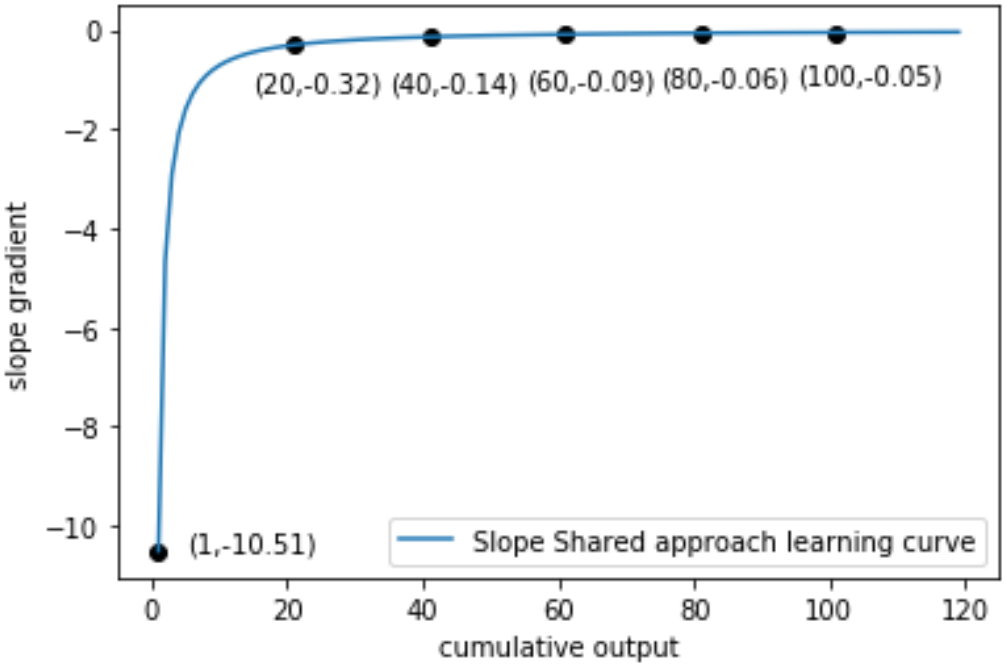

Figure 56: Shared approach learning curve slope

Analysing the slope shows that after 80 iterations, the slope increases only by 0.01 for 20 iterations. For the first 20 iterations, an increase of 10.09 is calculated.

5.5.4 Human-Centred vs. System-Centred and Shared Approach

The learning curves are shown in Figure 57 where the human learning curve has the least improvement compared to the learning curve of the shared approach which offers the biggest possible improvements. This can be explained by analysing the learning slopes of the parameters, where the slope of the task parameter is between 10 and 20 times higher than the slopes of the human parameter. This leads to bigger improvements for the task centred learning curve. The plotted learning curves show that the biggest improvements can be made by changing the task itself, which is obvious as an easier task is mastered faster than a difficult one. The least possible improvement is possible for the human-centred learning curve. This can be explained by the complex tasks in modern production systems that require a high amount of

knowledge and skills to be controlled properly. The system-centred learning curve has a greater slope compared to the human-centred learning curve but a smaller one than the task-centred learning curve, which is due to the ability of task support systems that help workers to master even very complex and difficult tasks.

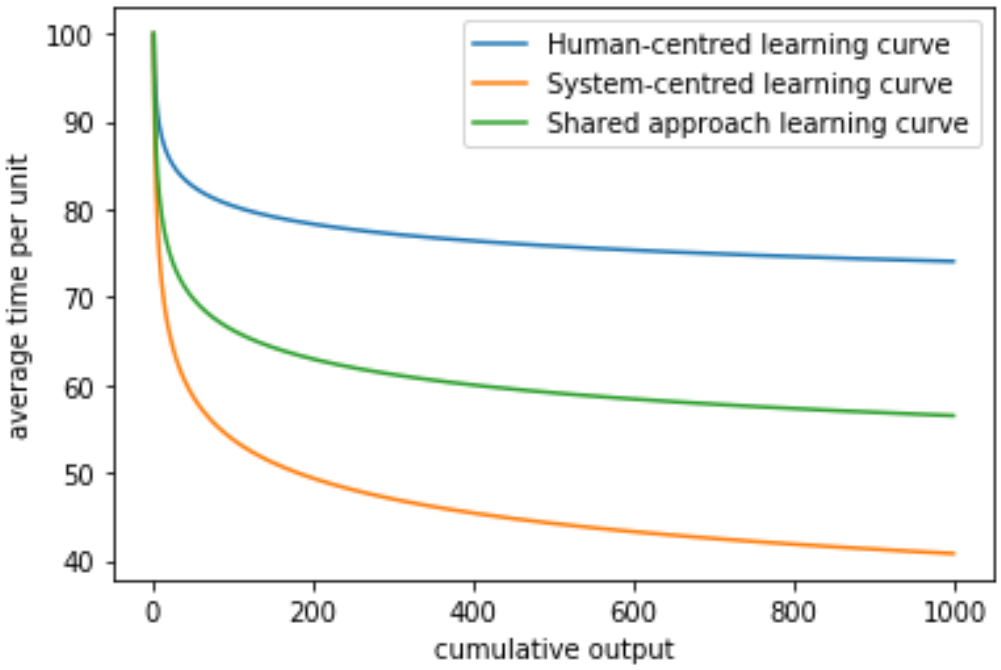

Figure 57: Comparison of the developed learning curve models

The learning curves plotted in Figure 57 were created by using the developed learning models and an initial value C_1=100.

5.5.5 Key Performance Indicators

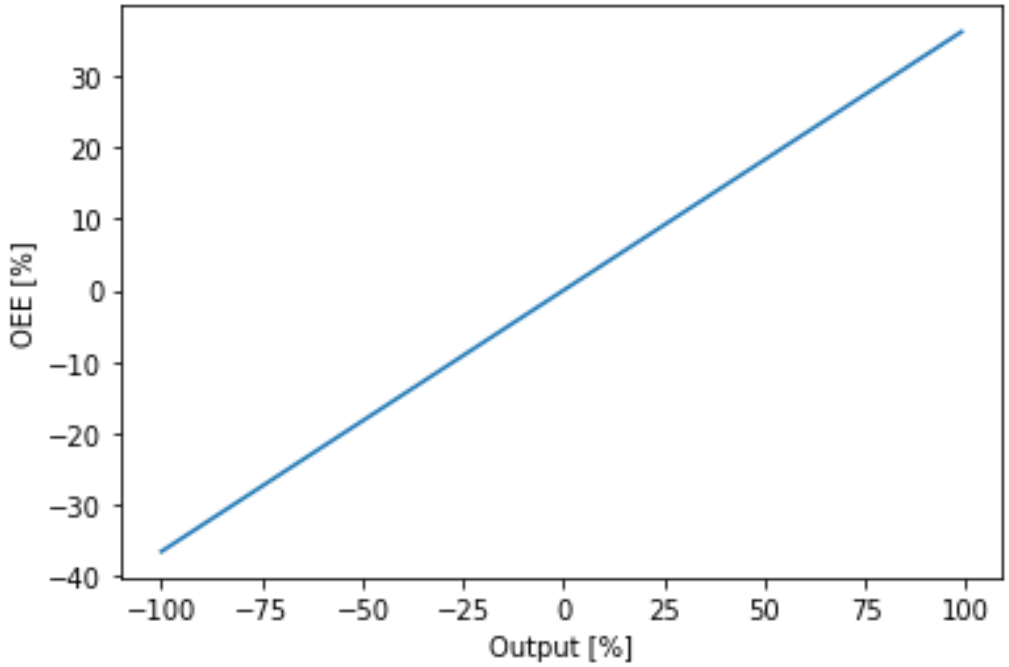

Figure 58: Change in overall equipment effectiveness related to changing output

Overall equipment effectiveness is a linear function of the change in output, the result of an improvement along a learning curve. A doubling of the output would result in an improvement of the OEE by 36.7%.

By using Formula 23, which describes the influence of the change of output along a learning curve and its effects on the OEE performance indicator, it is possible to derive for the learning curves evaluated earlier a relation towards the change in OEE. The OEE is dependent on the learning curve itself and the number of repetitions of a certain task, which results in a change in output. As the system-centred learning curve has the steepest learning slope, it results in the biggest change of the overall equipment effectiveness. After 100 repetitions, the OEE is rising by 12.4% for the shared approach learning curve, whereas the human-centred learning curve produces an improvement of 7.2%. Figure 59 shows the influence for the three learning curves developed. The range of improvement varies between 7.2% and 16.9% for a number of 100 repetitions.

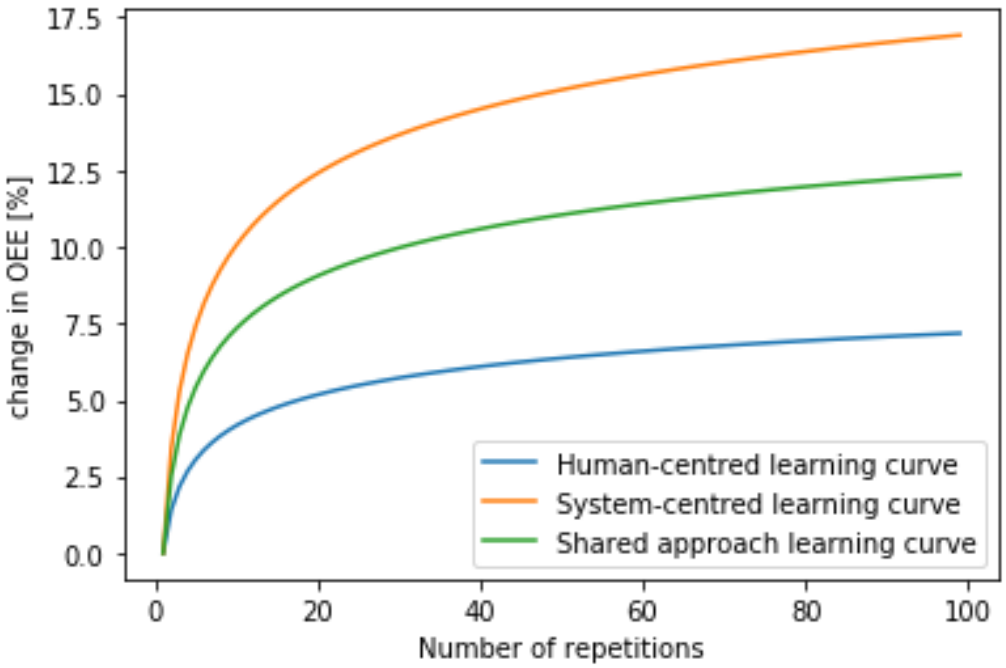

Figure 59: Influence of the number of repetitions on the OEE

5.6 Credibility of Results

Cantot and Luzeaux define credibility of a designed system as the relevance that the user sees in a model and the confidence the user has that a model or simulation can serve his purpose.[217] To demonstrate the credibility of the achieved results presented in 5.5, an analysis of the factors influencing the credibility of the whole process is outlined in this chapter.

The **usefulness** of the developed model has been demonstrated in detail in chapter 1.1. Human learning is becoming more important as employees need to handle complex systems and share their work with smart entities. For companies it is important to train their employees in such a way that they achieve the skills required for their position. In terms of efficiency a tool to evaluate learning for different configurations of the learning environment could be beneficial. Not only could the fastest way of bringing an employee to a certain level of knowledge be evaluated but also the combination of different factors improving the learning performance. In terms of financial advantages, this could be a major factor to estimate necessary costs for trainings, work support systems or the help of senior colleagues. Another aspect is the possibility to predict the long-term savings through improvements along the learning curve and therefore a performance improvement. To reflect these gains, a connection towards KPIs has been established in the application of the model in a maintenance use case.

[217] Cantot and Luzeaux (2011).

The evaluation of the **considered fields of study** can be divided in two sections. On one side, the learning theories together with the available learning curves to predict improvement through task repetition. On the other side the studies of digitalized industrial work scenarios in Industry 4.0. that provide a framework to model the human-machine interaction in an industrial environment. Starting with the learning domain, the provided theories originate in a psychological and neurophysiological environment. The learning curve concept, introduced in 2.24.4, that in our case is the link between the influencing factors and the change in performance has been widely used since its introduction by Wright in 1963 to predict performance changes in diverse working scenarios. The part expanding the learning curve model for the usage in an industrial work scenario in Industry 4.0. is based on studies about the complementarity of human and CPPS, especially the vector of competence and autonomy based on studies from Ansari & Seifenberg (2016).[218]

For the predictive learning model development, the **used methodology** is presented in 4.1. Every step has been conducted according to scientific best practices starting with the data collection through literature research. The factor classification is based on studies about the decision making in CPSPS expanded by the task dimension. An analysis of available learning curve models has been performed and a learning curve model suitable for the usage in CPSPS has been proposed. An optimization of the learning curve model has been performed using an analytic hierarchy process together with a feedback loop to improve the model optimization.

The **data used** for the calculation of the learning curve slopes was collected through a literature research of scientific studies. The studies were performed in industrial and educational environments which means that they are suitable for the application in cyber-physical-social production systems. All the used studies were published from researchers of known educational and research facilities. The transformation of the collected data has been performed with basic mathematical operations to represent the data in a comprehensible and comparable way. The whole transformation process and representation is documented in 4.2.

Encountered problems along the model development have been addressed as they occurred along the development process. Either a solution has been provided or a way forward to address the issue in the future has been presented. Furthermore, the possible ways of implementation of the developed model as well as the limitations are presented in 6.3

Achieved **Results** for the application of the developed predictive model are presented in 5.5. As discussed later in chapter 6.3, the magnitude of the values may lack accuracy being based on the assumptions taken for the researched use case. Nevertheless,

[218] Ansari and Seidenberg (2016, p. 313).

they are comparable due to consistent application of the data in this thesis. This allows to draw conclusions for the researched scenarios. As stated by Leung (2015), a margin of variability for results is tolerated in qualitative research provided the methodology and epistemological logistics consistently yield data that are ontologically similar but may differ in richness and ambience within similar dimensions.[219]

The presented results were achieved through scientific research and application of the gained knowledge to model the learning process for human-CPSPS interaction in a representative way. Throughout the whole process, all the steps have been documented in order to be able to reproduce the achieved results and verify the correctness of the used methods.

[219] Cf. Leung (2015, p. 326).

6 Conclusion and Outlook

The results obtained by applying the developed learning curve models to a maintenance use case are displayed in chapter 5.5, as well as the effect on the maintenance key performance indicators. The discussion section 6.1 tries to explain the achieved results and how they relate to the literature mentioned in chapter 2. The research questions defined in 1.3 are answered and the practical implications are deducted in 6.2. Limitations of the developed models are identified, and solutions are provided in 6.3. The following conclusion section 6.4 summarizes the main points and presents the findings of this thesis in an understandable way. Further directions of research are elaborated. Figure 60 displays the structure of this chapter.

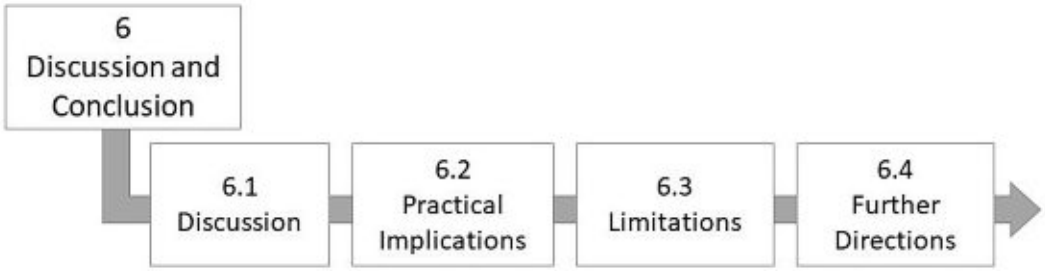

Figure 60: Structure of Chapter 6

6.1 Discussion

Cyber-physical-social production systems offer the possibility of learning processes taking place. Shown by Ansari et al. (2018), learning can occur between humans, humans learning from the system or the system learning from humans.[220] All these learning processes are influenced by factors present in a CPSPS identified in 2.3. Existing learning curve theories only allow the implementation of a limited amount of factors and are therefore not suitable for prediction of learning outcome in CPSPS. The developed model tackles this issue and allows the prediction of learning outcome based on selected influencing factors available in a CPSPS. The classification of the factors into a human, system or task category allows to identify the influence of the factors on the main actors of the learning process and therefore the learning curve. When analysing the learning rates included in the developed learning model displayed in Formula 15, the learning rate slope deducted from the human influencing factors is the lowest with $b_{Human} = 0.02$, the slope calculated for the system is eight times higher with $b_{System} = 0.155$ and the slope for the task being twice the value of the system slope with $b_{Task} = 0.283$. As hypothesized in research question 1 (RQ1) defined in 1.3, the learning curve is directly influenced by the factors present in a CPSPS. Furthermore, it shows that the task category has the highest learning slope with

[220] Cf. Ansari, Khobreh et al. (2018, p. 92).

changes in the task complexity influencing the learning curve the most. An explanation for this determination is that an easy task can be mastered very fast compared to a complex one which takes a large amount of time to be performed in the most efficient way. The comparatively lower slope of the human influencing factors versus the higher slope of the system factors can be explained through the ability of supporting the human working and learning process by the system. The human learning process can only be slightly changed by human influencing factors as we are limited. Technological means, on the other hand, offer possibilities that exceed the human capabilities by far and therefore offer greater potential for improvement. The expected results included a possibility to determine the improvement of a learner based on the factors present in his working and therefore learning environment. This has been achieved by the development of a learning curve model that allows to classify the present influencing factors and predict their influence on the learning curve. It is important to mention that contrary to the expected results, the model does not take into account the dependencies between the influencing factors. These dependencies must be researched individually by isolating certain factors and analysing the change of affected factors.

The influence of the factors on the learning curve and the application in a CPSPS have been elaborated in this chapter. An important point which still remains is how to measure the improvements of the learner. Key performance indicators are used for performance monitoring in the industry. They can be used to measure different kinds of performances, for example maintenance, energy etc.[221] Research question 2 (RQ2) defined in 1.3 targets the application of such key performance indicators to measure improvements through learning. KPIs can be used to register such changes and allows to analyse the changes in an economical way. To calculate key performance indicators, an analysis of the considered process is necessary. After all the relations between changes along the learning curve and KPIs have been established, it is possible to predict performance improvements based on the factors influencing the learning curve. Results vary depending on the application. For the considered maintenance use case described in 5.1.1, an improvement of 7,2% of the overall equipment effectiveness was predicted for a human-centred approach. This may seem small, but every prevented equipment breakdown or reduced downtime has a high potential for savings. The occurring costs in such a case easily overweigh the costs necessary to improve and ensure high equipment effectiveness. The expected results in 1.3 mentioned the possibility to observe the improvements through a change of the key performance indicators. This feature has been partially achieved through the implementation of a connection from the learning curve towards the KPIs for a specific use case. Unfortunately, this needs to be adapted for every considered example separately. The developed dashboard offers the possibility to select the affected KPIs and therefore

[221] Cf. Lindberg et al. (2015, p. 1785).

guarantees a flexibility for a certain range of tasks, such as maintenance tasks in this case, where the KPIs remain the same.

Cyber-physical-social production systems are characterized by a human-centred approach that focus on human beings and their environments.[222] A human-centred approach leaves the decision taking authority with the human compared to a system-centred approach, where the system has a high enough degree of autonomy to take the decisions. A middle ground is the shared approach in which human and system are equal in decision taking. Research question 3 (RQ3) deals with the possibility of human learning curves for the different approaches. The approaches result in different learning curves, as shown in 5.5.4. A human-centred approach has a lower and less steep learning curve compared to a system-centred approach. Due to the immense knowledge base and the ability to analyse the most optimal solutions for a given problem, the system is able to take the right decisions faster and more reliable. As a result, the learning curve for a system-centred approach is steeper and results in a higher outcome than for a human-centred approach. The shared approach with equal decision taking authorities between the human-centred and system-centred approach. A prerequisite that needs to be defined for the discussion of a system-centred approach is that the system needs to possess a high enough degree of automation. The expected result included the possibility to differentiate between a human-centred and a system-centred approach, which has been achieved by using an analytic hierarchy process allowing to define the decision-making authority in charge. This feature will have a rising importance in the future with rising degrees of autonomy for future production systems.

6.2 Practical Implications

The initial idea for developing a predictive learning curve model to use in cyber-physical-social production systems was to calculate the improvement of the learner or worker when considering typical factors present in a CPSPS. Throughout the model development and the connection to the key performance indicators, other implications for the usage came up.

The main application of the developed model is its predictive function in terms of forecasting the improvement due to learning in a CPSPS. The prediction is based on the influencing factors present in a CPSPS. In combination with a dashboard as displayed in 5.4, it is possible to predict the improvement of the key performance indicators based on the factors present and the number of repetitions of the task performed.

[222] Cf. Hadorn (2016, p. 3).

Especially the availability of a dashboard allows the plant operators to simulate several learning processes with various configurations. A configuration consists of a specified amount of influencing factors in place such as work assistance systems that support the worker, long breaks between the tasks or the team configuration. This offers the possibility to perform a fast economic analysis during the design phase of working processes.

The design of new industrial processes requires production planners to evaluate the necessary trainings and required workforce. Based on comparable processes in place and the required improvement, the necessary factors in place can be calculated upfront. This advantage would be beneficial in the early phases of the introduction of new workflows.

Changes in the available workforce in terms of education, capabilities or availability are a possible scenario for every kind of industrial application. These kinds of changes may force a turn from human-centred towards more system-centred production systems. The decision taking authority would over time move from humans towards the system. A predictive human learning model would help predicting the change in performance provoked by such a change in decision making. Furthermore, the planned change from human-centred towards system-centred can be accompanied by a predictive learning model to determine the necessary configurations and available tools in place to ensure a steady output and performance.

6.3 Limitations

The implementation of the developed model creates the possibility to predict the outcome of the learning process based on the influencing factors in place. Nevertheless, the following points should be considered when applying the model.

The influencing factors identified have not been researched in an isolated environment meaning that it cannot be excluded that other unidentified factors had an influence on the learning outcome. With the application of the learning curve not being performed in isolated environments either one can conclude that the influence of not considered factors is equalized. Furthermore, all the results obtained were acquired from the same basis of data so that the drawn conclusions are valid.

The influencing factors used for the model development were partially researched in non-industrial environments. To ensure the researched learning curve slopes are accurate, these factors should be verified in an industrial environment. Nevertheless, one can assume that the researched values are acceptable as the learning process is not dependent on its surrounding but on the duration and intensity of the stimuli described in 2.2.1.

A limitation present when considering CPSPS is the necessary degree of autonomy of the system as well as the level of competence of the user. For the development of a model to predict human learning in a CPSPS, the influencing factors need to be accurate. They rely in a high degree of the level competence of the learner and the degree of autonomy of the system.

The analytical hierarchy process is sensitive towards false comparisons resulting in wrong weights being attributed to the factors. Especially in early phases of the model application a monitoring is necessary to measure the obtained improvements, compare them against the simulated results and feedback the difference into the comparison. The proposed feedback process is presented in 4.6.

The developed learning model offers a framework to predict learning in a cyber-physical-social environment. The offered framework needs to be adapted for every process it is applied to. Ensuring that all the applicable influencing factors are selected and the researched process is correctly depicted to accurately predict the KPIs.

6.4 Further Directions

The developed learning curve model for human-centred learning process is a first step towards predicting learning in a highly interactive environment. It offers advantages compared to traditional learning evaluation techniques defined in 3.1. The possibility to connect the learning outcome towards measurable performance indicators creates an interest to use it in industrial applications. Its application together with tools such as a dashboard implementation offers the possibility to analyse and compare possible setups of industrial processes.

The model offers a solid basis for the development of other evaluation tools with more sophisticated characteristics. The design offers the possibility to implement other characteristics present in CPSPS such as environmental influences and the individual influencing factors of the learning curve. The used hierarchy can easily be adopted and completed by other influencing factors.

The model allows the application on other industrial processes by adapting the depicted process and adjustment of the model weights according to the respective use case. In case of changes in the setup, irrelevant factors are easily neglected by adapting their weight in the model.

Further steps would include the use of adequate sensors to implement a real-time monitoring of the learning process. This would allow to adopt immediately in case of problems with the learning process. Alternative support could be delivered to the learner or the environment could be adapted to guarantee the best learning output. Another major improvement would be the creation of a knowledge database including

factors and their interferences. Such a database would allow to implement the developed human learning curve model on every possible use case without being required to analyse the dependence of the factors on each other.

To sum up, the developed learning model offers the possibility to predict the learning outcome in a cyber-physical-social production system. Its application still requires a certain amount of time and data to fine-tune for the considered process. Nevertheless, the model offers a first way to implement such a prediction tool in an industrial environment.

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