Competency Management and Development in Manufacturing Companies – Results from Survey and Simulation Studies

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Summary

Companies and their employees will have to adapt to a changing working environment in the future. Global megatrends are particularly responsible for this, and new technologies are certainly an important factor. They will change the demands placed on companies and employees, in particular in the 21st century. As a consequence, some jobs will be replaced by automation, while others will be enriched by more complex activities. Additionally, a large part of the employees, particularly in industrialized countries, will leave the labor market due to progressing demographic effects. Therefore, companies will be left without important competencies that they had relied on for years. On the other hand, these technologies will help to cushion the newly emerging complexity through virtual assistance systems. However, it is expected that the average older population will find it more challenging to work with new technologies. Furthermore, globalization is resulting in increased dynamics and competitive pressure through global markets, which will also lead to a higher volatility in business operations (e.g., in demand). These trends will greatly change the world of work, especially requirements for employees and their competencies.

Therefore, this dissertation addresses the increased importance of managing employee competencies for manufacturing companies. The decision to obtain the appropriate employee competencies is an investment decision for companies which enables them to survive under these changed competitive conditions. On the one hand, companies need to know which competencies they require. On the other hand, they have to decide whether to train their existing employees for these competencies or to look for new employees who already possess them. Both are very time-consuming and cost-intensive processes.

This dissertation contains two parts. First, a comprehensive overview of this dissertation is provided. Within this overview, the motivation of the topic, an overarching research model, theoretical concepts, selected research methods, key findings and contributions as well as a summary of findings and the conclusion are outlined. Second, the four Research Papers (RPs), based on simulation studies, as well as a large survey with managerial participants are presented. Both approaches propose solutions and insights for competency management and development in manufacturing companies in order to enrich the theoretical and practical knowledge in this area. A short summary of each Research Paper is given below.

Research Paper 1: Competence management in the age of cyber-physical systems

The first paper provides profound theoretical contributions to the existing body of literature. The so-called cyber-physical systems are one fundamental part of Industry 4.0 technologies. As the environment of manufacturing companies is changing, the role of the employees, the content of

their tasks, and their duties are also changing. The automation and connection of simple manufacturing processes will increase the number of jobs with high technological and contextual complexity. Within this article, the impact on competency management of cyber-physical systems and how this influence can be represented in a competency rating instrument are elaborated.

Research Paper 2: The monetary value of competencies: A novel method and case study for smart manufacturing

Research Paper 2 also focuses on the working world of production and its changes due to new technologies. Therefore, the second article of this thesis provides two substantial contributions for the valuation of future competencies needed by mechatronic technicians in manufacturing companies. The first contribution is a monetary-based measurement method to determine the value of future work-related competencies. The second contribution is a case study. In this case study, the value of competencies of mechatronic technicians is assessed. The aim is to determine which competencies at which level bring additional monetary benefits in order to master the challenges posed by Industry 4.0 for this group of blue-collar workers. Especially the competency "complex-problem solving" is seen as very valuable. Several categories of knowledge also get higher monetary values than other groups. Noteworthily, different groups involved in the hiring and training process of mechatronics value competencies significantly differently.

Research Paper 3: Consequences of the interplay between volatility and capacity for workforce planning and employee learning

Demand fluctuations arising from customer requirements, new technological developments, individualization, shorter lifecycles etc. have an enormous impact on business processes. These developments also lead to an increasing number of production ramp-ups. For the success of ramp-ups learning is crucial. Therefore, within the third paper, the impact from demand volatility and the interplay with employee capacity on learning-by-doing, training, forgetting, achieved skill levels, and efficiency gains of shop-floor employees are analyzed. It is shown that demand volatility has a significant impact on skill development. In several cases, the impact of demand volatility on the learning behavior of employees depends on the available employee capacity.

Research Paper 4: Workforce planning in production with flexible or budgeted employee training and volatile demand

Investments in workforce learning and training measures are crucial for the success of production ramp-ups. In this phase, new requirements occur which often make the adaption of employee competencies necessary. Traditional training approaches are commonly limited to a defined period at the beginning of a production ramp-up and are restricted to the respective training units. Training concepts of a more flexible nature can help to overcome challenges for skill development during production ramp-ups. Therefore, budgeting and non-budgeting of training measures are analyzed in the same scenario as in Research Paper 3. The budgeting of training has a negative impact on skill development. The interactions of budgeting with demand volatility and employee capacity show further interesting implications for the decision to implement employee training measures in shop-floor settings.

In summary, the present dissertation extends the existing research in two thematic strands: competency ratings and value (Research Papers 1 and 2) and competency development (Research Papers 3 and 4) in manufacturing environments. It provides theoretical as well as managerial implications on how the employee's competency development process is impacted by demand volatility and restrictions from employee capacity. Furthermore, it provides tools for organizations to steer the synchronization between their current organizational and employee competencies and the future needs resulting from the impact of various megatrends that will change how we work.

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List of Abbreviations

AR-1	First-order autoregressive working correlation structure
B	Unstandardized regression coefficient
BIC	BIC (Bayes information criteria)
Cap	Capacity
CPS	Cyber-physical systems
EFS	Enterprise Feedback Suite
et al.	et alia (and others)
etc.	et cetera (and so on)
e.g.	exempli gratia (for example)
GAMS	General Algebraic Modeling System
GEE	Generalized Estimating Equation
H	Hypothesis
HR	Human resource
i.e.	id est (that is)
IfM	Institut für Mittelstandsforschung Bonn
KSAO	Knowledge – Skills – Abilities – Other Characteristics
LMM	Linear mixed model
M	Mean
Min	Minimal
MIP	Mixed Integer Programming
N/n	Number of observations
O*NET	The Occupational Information Network
Opt	Optimal
OR	Operations Research
p	p-value
p.	page

pp.	pages
PhD	Philosophiae Doctor (Doctor of Philosophy)
POMS	Production and Operations Management Society
Prod	Production
RP	Research Paper
RWTH Aachen	Rheinisch-Westfälische Technische Hochschule Aachen
SD	Standard Deviation
SE	Standard Error
SME	Small and medium-sized enterprises
Vol.	Volume
vs.	versus (against)
VUCA	Volatility – Uncertainty – Complexity – Ambiguity

I Comprehensive Overview

This dissertation deals with competency management and development in manufacturing companies. This first part gives a comprehensive overview of the dissertation project. The second part contains the four research articles, in which, separately, the respective research contributions of this dissertation were made.

1 Introduction

Manufacturing companies face several changes that have an impact on how employees will work and learn in the future; this affects which competencies are needed and how these competencies will be acquired. For this purpose, it is important to consider the factors influencing manufacturing companies. This chapter shows the motivation of this dissertation and briefly discusses several important trends that have an impact on manufacturing competencies in the 21st century. It further provides an outlook on the requirements of the work of the future. Afterwards, the research contributions of this dissertation project will be discussed.

1.1 Megatrends Shape the Production of the Future

Production systems are often highly dynamic socio-technical systems that can only survive and compete if they adapt to the environment which is changing dramatically in the 21st century (Westkämper and Löffler, 2016). The main reason are global megatrends, which will also have an enormous influence on the way, place, and content of industrial work (Horx, 2007).

Whereby the contents vary depending on the author slightly. According to Gatterer (2019), in the near future, five megatrends will be particularly important for companies: Individualization, aging, digitization and connectivity, urbanization and knowledge culture. Westkämper and Löffler (2016) list eight megatrends with a direct impact on production: increasing world population, aging society, urbanization, sustainability, individualization, knowledge and information, globalization, and changing financial conditions. Particularly technological progress, demographic change, and globalization may alter the world of work in the future (Helmold, 2021; Stock-Homburg, 2013). Companies, particularly their human resource departments, are not yet dealing sufficiently with the effects of these megatrends (Sauter and Scholz 2015). Beyer (2015) identified that human resource managers perceive digitization to be the main megatrend that will have a massive impact on human resource management activities. Furthermore, she identified changing values (e.g., increasing desire for sustainability), demographic change, and globalization as further trends with strong influence on human resource management. Hence, the megatrends of technological change, demographic change, globalization and new work will be addressed in more specific depth here.

Technological change, especially within production systems, will have a huge impact on employee work in the future. In Germany, these developments are summarized by the term *"Industry 4.0*[1]*."* Often, the buzzword Industry 4.0 summarizes technological developments such as cyber-physical systems (CPS), internet of things, big data, automation of production, digitization, smart factory, etc. (Bauernhansl, 2014; Lasi et al., 2014; Oesterreich and Teuteberg, 2016). According to Jäger et al. (2015), Industry 4.0 technologies can be divided into the three technology fields of cloud computing, cyber-physical systems, and smart factory. Furthermore, few organizations already understand the concept of Industry 4.0 in detail (Sony and Naik, 2019), especially since the definition chosen often depends on the context in practice and varies between academic disciplines (Ivanov et al., 2020).

Additionally, industrialized countries are impacted by the consequences of their aging workforce (Fornalczyk, Stompór-Świderska, and Ślazyk-Sobol 2015). Based on forecasts, it seems to be almost certain that the availability of employees will decline, as fewer potential candidates will be available in the job market. The majority of the current employees will reach retirement age and, therefore, retire from the workforce within the coming years (Blatter et al., 2016; Fornalczyk et al., 2015). Calzavara et al. (2020) argue that despite declining physical and cognitive competencies, older employees are still an important resource for their companies, as they often have many years of experience that cannot be replaced quickly. Consequently, it will be crucial for companies to retain important competencies in order to maintain industrial competitiveness (Calo 2008; Joe, Yoong and Patel 2013), especially because older employees possess competencies that they have developed over the years, e.g., coping with stress strategies (Johnson et al. 2013; Truxillo and Fraccaroli 2013). However, these older employees have to adapt to new technologies. Older employees learn less effectively and at a slower rate than younger employees (Picchio, 2021). Therefore, target-group-adequate training is necessary to meet the needs of older employees (Bauernhansl, 2014; Picchio, 2021).

Additionally, globalization integrates business processes, politics, and culture over the whole world (Abele and Reinhart, 2011; Westkämper and Löffler, 2016). This also enables an unhindered flow of goods, knowledge, and information across the entire world (Westkämper and Löffler, 2016). Therefore, a well-educated workforce is necessary to keep high-wage countries with low natural resources, such as Germany, competitive (Abele and Reinhart, 2011).

[1] Within Research Paper 4 the term "smart manufacturing" is used instead of Industry 4.0. For Part 1 of this dissertation, only Industry 4.0 is used. "Smart manufacturing" is more common in English speaking countries (Sniderman et al., 2016). In Germany, the term Industry 4.0 is quite popular.

Globalization also means that product life cycles are becoming increasingly shorter as a result of changing customer demands, and companies have to cut costs in order to remain competitive (Spath et al., 2013). According to Westkämper and Löffler (2016), the requirements of the markets are the main drivers for change within production systems. The increasing volatility of demand is also mentioned as a recurrent theme. This is further driven by internationalization and customized production resulting in an increase in the number of variants produced (Westkämper and Löffler, 2016).

The current pandemic (COVID-19), which has given digitization an additional boost in some companies, is certainly an accelerator of changes in the world of work besides these already existing influence factors (Helmold, 2021). To attract new talents in order to stay competitive, companies also have to deal with the megatrend "New Work" (Bergmann, 2019). New Work catering to the needs of employees who enjoy being more creative, more demanding, more self-determined, more freedom-based and more flexible (Bergmann, 2019). Work 4.0 is also frequently mentioned in this context. However, the term is more closely related to the changes brought about by Industry 4.0 (Barsch and Trachsel, 2018). Furthermore, young workers increasingly have a desire for work-life balance and flexibility (Stock-Homburg, 2013). Additionally, role perceptions in society are changing. In recent years, women have also been increasingly striving towards a career, and this will also require companies to respond more to the needs of both mothers and fathers (Stock-Homburg, 2013). For instance, in many countries, the number of men who take parental leave is rising (OECD, 2016). Fathers' use of parental leave, however, is influenced by the family-supportiveness of their work environment (e.g., Haas and Hwang 2019). Moreover, among fathers who take parental leave, the ones who perceive their company to be family-unsupportive worry more intensely about the work-related consequences of their leave than the ones who perceive their company to be family-supportive (Stertz et al., 2020). The sense of commitment towards companies is changing and the company that can offer a candidate the most financially or the most in terms of job content will be the one that the candidate signs a contract (Stock-Homburg 2013).

Overall, these trends are also changing the demands placed on employees (e.g., Schinner et al. 2017; Letmathe and Schinner 2017; Beyer 2015; Frey and Osborne 2013), and several challenges are arising from these megatrends for manufacturing companies. These challenges, in turn, have an impact on human resource management (Hecklau et al., 2016). Lin, Chiu, and Chu (2006) argue that the entire supply chain of companies must be re-organized towards greater agility, in order to master changes in the corporate environment (in this case: market requirements, technological innovation, competition criteria) and in order to remain competitive. To react to these developments, the increase in competencies and flexibility are particularly important factors for the competitiveness of companies (Lin et al., 2006).

1.2 Requirements on the Future Workplace and the Competencies of Employees

Several studies have already focused on the changes in the workplace of the future, owing to new technological developments like Industry 4.0. The study of Frey and Osborne (2013) is particularly notable. The authors showed that 47% of jobs in the US have the potential to be substituted by automation. Furthermore, the nature of jobs will shift with these developments, and employees will be required to adapt in order to remain employable in the job market.

However, it is certain that these new technologies will change how we currently produce goods. Moreover, the future workforce in manufacturing companies will face several economic, social, technical, environmental, political, and legal challenges (Hecklau et al., 2016; Hirsch-Kreinsen and ten Hompel, 2017). According to Adolph, Tisch, and Metternich (2014), workers face increasingly complex situations and have to prove themselves in unfamiliar situations. Routine tasks will decrease and several jobs will face the risk of automation (Frey and Osborne, 2013). Vice versa, Industry 4.0 aims to meet current challenges such as increasing global competition, volatile markets and requirements, necessary adjustments, and even shorter innovation and product lifecycles (Müller et al., 2018). According to Autor and Dorn (2013), low-skilled individuals, who perform routine tasks, will switch to service jobs that require more communication and interaction, dexterity, and direct physical proximity. Highly educated employees will perform tasks with creative, problem-solving, or coordination content as manufacturing becomes increasingly automated (e.g., Bonin, Gregory, and Zierah 2015; Dworschak et al. 2013; Frey and Osborne 2015; Letmathe and Schinner 2017; Ras et al. 2017;).

According to Kölmel et al. (2014), employees have to handle increasing contextual and technological complexity in this context. An example of technological complexity is when employees face a complex system architecture. By contrast, examples of contextual complexity are broader job profiles with less routine tasks. With the task content, the requirements on competencies will change. However, the challenges posed by new technologies manifest themselves in many ways. Ras et al. (2017) argue that the roles of the employees through the use of intelligent assistance, such as augmented reality, will be more data- and knowledge-driven and their complexity will increase. Some processes will run completely autonomously without employee intervention, or employees will only intervene when problems need to be solved (Smids et al., 2020). However, algorithms and computers will not only replace routine tasks but will also be able to replace non-routine tasks. The full potential of change due to these technologies is probably not fully predictable (Brynjolfsson et al., 2014; Brynjolfsson and

Mcafee, 2011). Moreover, demographic change and changing values of the workforce, along with the increasing digital work and the growing complexity of processes are a social challenge for employees. Aging employees are impacted very individually by the aging process. For some of them, aging can have an impact on their senso-motoric, sensory, and cognitive capabilities and they lose the ability to perform certain tasks. Additionally, learning a new task becomes harder with age (Craik and Salthouse, 2011; Li and Lindenberger, 2002). Furthermore, globalization makes it necessary for individuals to work in intercultural teams (Hecklau et al., 2016). For instance, forms of collaborative work such as virtual teams and video conferencing systems will be increasingly used to promote global exchange between employees due to globalization (Stock-Homburg, 2013). In addition, legal challenges, e.g., data security or personal privacy, are also new issues to be handled which increase complexity for the workforce of the future (Hecklau et al., 2016).

Vice versa, the new technologies of Industry 4.0, in particular, can help to counteract the increased need for flexibility due to, for instance, individualization and shorter product life cycles as well as turbulences due to volatile market demand (Müller et al., 2018). Moreover, digital and continuously available adaptive training that is integrated into academic and vocational training is also conceivable. For example, the learning content can be linked to the work process and the employees can control the learning process by themselves as opposed to learning in a classroom. Depending on their progress, additional information can be included from the context that goes beyond the original learning objective. In addition, there are many more connecting points through these new technologies, and they offer an enormous potential (Kuper, 2020).

1.3 Research Contributions

Changing requirements will make industrial production highly dependent on the competencies available in the market (Westkämper and Löffler, 2016). As already mentioned, also the availability of competencies will decline with an increasing number of retired people (Blatter et al. 2016). Three developments in industrialized countries, namely unclear qualification needs due to technological change (Letmathe and Schinner, 2017; Pfeiffer, 2015; Pfeiffer et al., 2016), expected skill shortages due to demographic change (Blatter et al., 2016; Cappelli, 2015), and changing requirements for the workforce of the future (Stock-Homburg, 2013) increase the need for action in this area. Consequently, it is important to find out which competencies and dimensions of competencies are important and valuable for manufacturing companies in the 21st century. This is primarily focused in Research Papers 1 and 2 with three contributions and is therefore the first thematic strand of this dissertation.

Roles in work, content of work, and the way in which we work will change for manufacturing systems; so, too, will the competency requirements. (Dworschak and Zaiser, 2014; Frey and Osborne, 2013). One reason, for instance, is increasing complexity. The automation of simple manufacturing processes and the activities they involve will increase the number of jobs with high complexity (Hecklau et al., 2016). Furthermore, product complexity increases with fast changing technology and the continuous development of novel products (Simchi-Levi et al., 2008). The so-called cyber-physical systems specifically increase this trend (Kagermann et al., 2013).

Therefore, ***Contribution 1 of Research Paper 1*** *is the presentation of impacts on competency management through cyber-physical systems and how this influence can be represented in a competency rating instrument.*

Employee selection and development is a cost- and time-intensive process which requires several resources within companies (Blatter et al., 2016). Training of unskilled employees takes a lot of time and increases costs (Blatter et al., 2016; Cappelli, 2015). According to Seyda and Placke (2017), companies in Germany invested 33.5 billion euros in 2016 for continuing vocational education. Alternatively, companies could hire candidates with the appropriate competencies, who just need a little training (e.g., employees need at least firm-specific knowledge) (Blatter et al., 2016). After all, in many cases, choosing between putting more effort into training or into employee selection is an investment decision. On the other hand, if companies do not invest in the competencies of their employees, they must bear the opportunity costs if they are unable to perform in the market due to a lack of manpower.

Pfeiffer (2015) notices this conflicting idea among companies when they rank their talents and their competencies as the most important driver for global manufacturing competitiveness and, by contrast, rank cost competitiveness second, which is mainly driven by labor costs (e.g., Giffi et al. 2016; Roth et al. 2010). The same conflict is revealed in a study of the Association of German Chambers of Commerce and Industry. Companies rank the shortage of skilled labor as the greatest risk for economic development in Germany and rank the rise of labor costs due to higher wages second (DIHK, 2018). Furthermore, the cost-benefits of soft competencies are not or barely measurable e.g., in time improvement to obtain a monetary value (Cascio, 2008; Muehlemann and Wolter, 2014). Consequently, the management of hiring and training processes is becoming increasingly difficult for human resource managers. Autor and Handel (2013) show that job-tasks are significant predictors for the wage of an employee. The necessary competencies are required in order to perform these tasks. It is therefore obvious that the necessary competencies must also be valued in monetary terms to be able to make the decision (e.g., hiring vs. training) more accurately.

*Due to this, the **Contribution 2 of Research Paper 2** is a novel monetary-based measurement method to determine the value of future work-related competencies.*

Research on future competencies for smart manufacturing or 21st century skills is mostly focused on academic requirements and often neglects the training professions (Pfeiffer, 2015; Pfeiffer et al., 2016). Therefore, this dissertation analyzes learning and competencies with a particular focus on shop floor employees and examines which competencies are valuable for them.

Hence, ***Contribution 3*** is given in ***Research Paper 2***. *Within a case study on blue-collar workers, particularly from the field of mechatronics, their required competencies for Industry 4.0 are valued.*

The case study not only shows how to apply the new method for assessing work-related competencies but also provides important insights into how experts from different disciplines (i.e., HR management vs. production management) will assess future workforce competency requirements for blue-collar employees.

Furthermore, this dissertation deals with competency development in the second thematic strand within a ramp-up scenario. Companies have to respond fast and be cost-efficient towards customer requirements in order to remain competitive in this challenging time. The consequence are shorter lifecycles of products (Hansen and Grunow, 2015) and, as a result, an increasing number of production ramp-ups. Especially in ramp-up scenarios, these problems become much more severe, as this time span is key for the success of a product (Surbier et al., 2014). During this time, it is also particularly important for companies to integrate training measures for quickly training their employees. Moreover, the production capacity is low and the demand is high in this crucial phase (Terwiesch and Bohn, 2001). Therefore, as a restricting factor, employee capacity was used within the simulation studies. Lower employee capacity reduces the ability to respond to fluctuations in demand (Zhang, Song, and Yu 2012) and also leaves less time for training (Anderson 2001). Vice versa, capacity can be better utilized with a higher level of experience and competency. Due to fast changing market conditions, customization of products and changing customer expectations result quite often in volatile demand (Spath et al., 2013). Turbulences, like demand volatility, cause problems in companies, such as shortage costs (Kulp et al., 2004). Furthermore, they lead to an unbalanced learning-by-doing and training behavior, due to an unbalanced production program (Shafer et al., 2001). This disturbs the success of competency development in this crucial phase. Thus, it is important to deal with the consequences of demand volatility and restrictions during competency development in the second strand of this dissertation. The following research question was formulated for Research Paper 3:

Research Question Research Paper 3*: What is the impact of demand volatility and its interplay with employee capacity on the learning and training of employees in production ramp-ups?*

Additionally, to avoid shortages of skilled labor, the effort for employee search and development will increase. Consequently, companies should increase their internal training offers and develop their existing workforce (Blatter et al. 2016). In most cases, the hired employee needs training at least to obtain firm-specific knowledge in order to be fully productive (Blatter et al., 2016). Research Paper 4 is, to a large degree, based on Research Paper 3. A special focus is to gain more information on flexible training concepts with a constant availability of training measures in comparison to traditional training approaches. Due to changes in the environment of companies with new and often more complex tasks, companies have to adapt their competencies according to the requirements they face in the 21st century (Bonin et al., 2015; Frey and Osborne, 2013). Traditional training approaches are often limited to a short defined time period, usually at the beginning of a new activity or when new activities (e.g., production ramp-ups) become necessary due to changed processes (Ally, 2009). Therefore, the following research question was formulated:

Research Question Research Paper 4*: What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems?*

Taken together, these two strands and the respective research questions and contributions (see Table I–1) of the four research papers yield the overarching research question. The overarching research question of the entire dissertation is therefore:

Which competencies will be important and valuable in future production and how is competency development influenced by volatility and restrictions in production systems?

Table I–1: Overview of Research Contributions and Questions

Research Paper	Research Question / Contribution
RP 1	Presentation of impacts on competency management through cyber-physical systems and how this influence can be represented in a rating instrument.
RP 2	A novel monetary-based measurement method to determine the value of future work-related competencies. A case study on blue-collar workers, particularly from mechatronics, to identify their required competencies for the digital age.
RP 3	What is the impact of demand volatility and its interplay with employee capacity on the learning and training of employees in production ramp-ups?
RP 4	What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems?

1.4 Research Framework and Overview of Articles

In this section, the research framework is summarized, presented in a graphical overview (see Figure I–1) and afterwards a short overview of the articles (titles, authors, publication status and conferences or talks) is given (see Table I–2). This dissertation deals with the subject area of competency management in manufacturing companies. Companies are currently being influenced by various megatrends. Through these megatrends, the future workplace will have different requirements than now or in the past and how we work will change (Helmold, 2021; Stock-Homburg, 2013). The (global) markets, particularly, are strong drivers of change; the internationalization of markets is leading to a global arena and flow of goods (Westkämper and Löffler, 2016). Individualization is leading to more variants of products and more production ramp-ups. These trends are causing demand volatility and other turbulences. Employees will need to handle, in the future, an increasing contextual and technological complexity (Kölmel et al. 2014) arising from, for example, new production processes and automation. They will also need to handle collaboration with different cultures in order to solve problems in multinational teams due to the globalization of production facilities all over the world (Helmold, 2021; Stock-Homburg, 2013). This will lead to employees needing different competencies in the future than now or in the past. For example, problem-solving skills or the ability to work in multicultural teams will take on a completely different meaning (Leopold et al., 2018) This trend is further exacerbated by the fact that a majority of the current employees will reach retirement age and be leaving the job market through demographic change. With them, also their competencies will leave the job market, and the availability of employee capacity will decrease. Therefore scarcity of qualified labor will increase further hiring and training costs (Blatter et al., 2016; Fornalczyk et al., 2015). This makes it even more important to use resources (money, employee capacity, machines, raw materials, etc.) efficiently in order to survive in global competition and so that companies develop their capabilities, through, for instance, employee competencies, in order to react flexibly to these developments (Adolph et al., 2014).

Within the four research papers two main strands of answers are given regarding the challenges to manufacturing companies in the 21st century: competency ratings and value as well as competency development. The first strand of this dissertation shows which competencies are needed and how ratings or valuations for these competencies can be used. Second, the impact of demand volatility, employee capacity restrictions and budgeting of training measures on competency development is analyzed. Research on future competencies for smart manufacturing or 21st century skills is mostly focused on academic requirements and often neglects the professions of vocational education (Pfeiffer, 2015; Pfeiffer et al., 2016). Therefore, this dissertation analyses learning and competencies with a particular focus on shop floor employees.

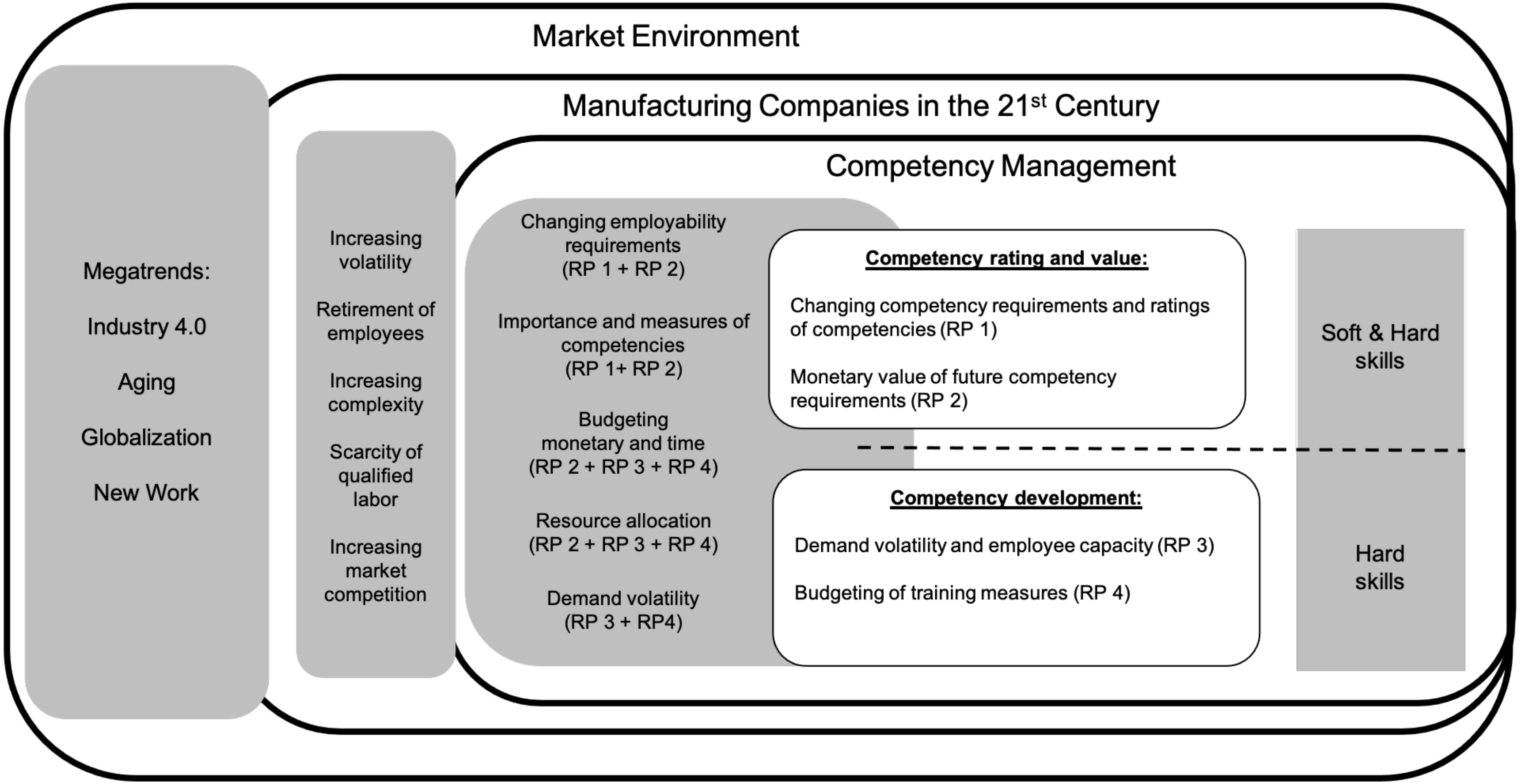

Figure I–1: Research Framework

The remainder of Part 1 of this dissertation is structured as follows: Chapter 2 explains the theoretical background, defines competency and competency models, and provides an introduction about competency development (learning-by-doing, forgetting, and training) in optimization models. Chapter 3 then deals with the methodological approach by providing an argumentation for the choice of simulation studies and using a survey study. Chapter 4 summarizes major contributions, hypotheses, and key findings of the four research papers. Furthermore, hypothesis tests of the Research Papers 3 and 4 are also presented in Chapter 4. Finally, in Chapter 5, a summary of the key findings, implications for theory and practice, limitations, and an outlook for future research are given. Part 2 then presents the four research papers. The formatting of the four papers in Part 2 differs due to different target journals (see Table I–2). All articles except Research Paper 3 (British English) are written in American English. Table I–2 provides an overview of the research papers included in this dissertation thesis.

Table I–2: Overview of Research Papers and Academic Visibility

Research Paper	Title	Authors[2]	Publication Status	Selected Presentations
RP 1	Competence Management in the Age of Cyber-Physical Systems	Letmathe, Schinner	Published 2017 in the book Industrial Internet of Things – Cybermanufacturing Systems	PhD Seminar Management Accounting
RP 2	The monetary value of competencies: A novel method and case study for smart manufacturing	Böhm, Letmathe, Schinner	Submission to the Journal Technological Forecasting and Social Change – planned	PhD Seminar Management Accounting, Doctoral Seminar University of Boulder Colorado
RP 3	Consequences of the interplay between volatility and capacity for workforce planning and employee learning	Letmathe, Schinner	Submission to the International Journal of Operations & Production Management – planned	POMS 2015 PhD Seminar Management Accounting, Doctoral Seminar Operations Management Clemson University, Doctoral Seminar University of Boulder Colorado, OR 2019
RP 4	Workforce planning in production with flexible or budgeted employee training and volatile demand	Heuser, Letmathe, Schinner	Published 2022 in the Journal of Business Economics	OR 2018, POMS 2019, PhD Seminar Management Accounting

2 Theory

This chapter presents the fundamental definitions and theoretical basis of this dissertation. Therefore, different competency definitions and possibilities for competency categorization will be defined. Furthermore, the fundamentals for competency development (learning-by-doing, forgetting, training) with focus on the relevant literature in the area of operations research (OR), are discussed.

2.1 Competency and Competency Management

There is still no universally valid definition of "competencies" (Fahrenbach et al., 2019). After McClelland (1973) showed the relevance of the term "competence," instead of focusing

[2] Authors in alphabetical order.

only on intelligence as a predictor of performance and success, several different definitions and perspectives were introduced for this abstract term. Due to this, Klink and Boon (2003, 126) call it a "confusing" or a "fuzzy" concept. For the classification of this term, Klink and Boon (2003) present three different perspectives that have at least some minor differences: geographic (e.g., Germany vs. US), learning theory (cognitivist vs. constructivist paradigm), and the field of application (e.g., training and education, employee selection, and performance assessment). It is obvious that the definitions of the term "competency" often depend on the research subject or the perspective of the user.

In Research Papers 3 and 4 the focus is on learnable competencies which can also deteriorate through forgetting over time. This is a basic requirement for the simulation of the competency development within the formulated quantitative model. The used definition is "*skills as the ability to perform certain tasks well*" (De Bruecker et al. 2015, 2). The emphasis is on performance because also the output is focused.

Research Paper 1 presents different definitions. The definition by Erpenbeck and von Rosenstiel (2007) should be emphasized (see Table I–3). It distinguishes competencies from knowledge. If someone has knowledge, it does not mean that the person can translate that knowledge into sufficient action. In this sense, competencies are dispositions of knowledge and skills. Competencies are thus fundamental abilities that enable the individual to act even in unfamiliar or unmanageable, new, and open situations (Erpenbeck and von Rosenstiel, 2007).

According to Sarges (2006), a precise definition for describing competencies was provided by Spencer and Spencer (1993, 9): "*A competency is an underlying characteristic of an individual that is causally related to criterion-referenced effective and/or superior performance in a job or situation.*" In our view, the causal relationship between behavior and performance in jobs is important because it determines the success and value for employers. That is also the reason why this definition was used in Research Paper 2. Because there is no universally accepted definition of competencies, different definitions in the four articles adapted to the respective object of investigation are used. Table I–3 provides an overview of the competency definitions mainly used in the different articles.

Table I–3: Competency Definitions Applied in the Different Research Papers

Research Paper	Overview of used competency definitions in the different articles	Source
RP 1	*"A person's competence basically describes a relation between requirements placed on a person/group or self-created requirements and these persons' skills and potentials to be able to meet these requirements. Competencies are concretized at the moment knowledge is applied and become measurable in the achieved result of the actions."*	(Reinhardt and North 2003, p. 1374)
	"skills are the abilities an individual has to do things. Competency is the set of skills that an individual can use in doing a given task."	(Sanchez 2001, p. 7)
	"dispositions for self-organization activities"	(Erpenbeck and von Rosenstiel 2007, p. XIX)
RP 2	*"competency is an underlying characteristic of an individual that is causally related to criterion-referenced effective and/or superior performance in a job or situation."*	(Spencer and Spencer 1993, p. 9)
RP 3 & RP 4	*"we define skills as the ability to perform certain tasks well."*	(De Bruecker et al. 2015, p. 2)

Klink and Boon (2003) highlight the usefulness of competency management to satisfy organizational needs through training or employee selection. Additionally, Reinhardt and North (2003) argue, that the competency portfolio on the individual level should be synchronized with the requirements of the organization and, especially, the used technology through training or education (Schinner et al., 2017). This process is the so-called competency adaption. It coordinates the adaption of individual competencies to meet the requirements of the organization (Reinhardt and North, 2003). Several competencies are enduring and not trainable. Consequently, Spencer and Spencer (1993) argue that companies should select employees with high motivation and appropriate traits because it is more cost-effective to train them for skills and knowledge. This is especially true because these soft competencies are often the predictors of superior performance. Unfortunately, most companies do the opposite: they assume that the candidates already possess the appropriate motivation and character traits and hire employees according to criteria such as knowledge or skills, which are more easily observable. Therefore, companies should plan their employee selection and training process carefully.

It is important to classify and structure competencies. Otherwise a synchronization of organizational and individual competencies would not be possible (Reinhardt and North, 2003).

Several different classifications are developed. According to Spencer and Spencer (1993), the underlying characteristics are knowledge, skills, self-concept, motives, and traits; they classify these characteristics in the so-called iceberg model. In this model, knowledge and skills are more visible and easier to develop through training than the core personality (traits, motives) of an employee, which is enduring. Especially the classification in hard (technical) and soft skills (intra- and interpersonal) is often used to describe differences between competencies on a simple way. Hard skills involve, for instance, working with technical equipment or software. Vice versa, soft skills are, for instance, the ability to manage oneself (Laker and Powell, 2011). Another often used classification of individual competencies is professional competencies (technological and, in part, methodological competencies), personal, and soft competencies. Therefore, this approach for classification was adopted in Research Paper 1. Competencies are often divided into technical, methodological, social, and self-management competencies. This classification, often used in the European context, is action oriented (Fahrenbach et al., 2019).

To analyze competencies, several companies use competency descriptors that contain different knowledge, skills, abilities, and other characteristics (KSAO) (e.g., Campion et al. 2011). Additionally, the "Occupational Information Network" (O*NET) uses a similar approach with measures for knowledge, skills, abilities, work activities, training, work context, and job characteristics. These can be worker orientated or job orientated (Peterson et al., 1999). Another distinction would be knowledge, skills, and competency (Le Deist and Winterton, 2005). The O*Net taxonomy (widely used in the USA) is more descriptive (Fahrenbach et al., 2019).

In Research Paper 2, a KSAO adoption from the O*NET taxonomy is used, because the O*NET database is undoubtedly the most internationally recognized and up-to-date job database, with several extensive descriptors (Fahrenbach et al., 2019). Different facets of content-specific knowledge or technical expertise often represent hard skills or technical competencies that employees must possess to fulfill their job duties (Robles, 2012), e.g., mechanical knowledge. The definitions of the skill vary (Tippins and Hilton, 2010) and depend on the perspective of the research subject. Often, the category "skill" is related to procedural knowledge (Brannick et al., 2012). Furthermore, skills depend on experience and education and are not a permanent characteristic of an employee by default (Peterson et al., 1999). Abilities are traits that may develop over time but can also exhibit a sustained stability over several periods. Vice versa, skills depend more on the training and development of an individual and are more situational (Peterson et al., 1999). For other characteristics, we use work styles because they are important predictors of work readiness (Golubovich et al., 2017). Further, Taylor et al.

(2008) illustrate the importance of work styles for describing job requirements, for the planning of training measures, as well as employee selection. The categories "abilities" and "work styles" are more enduring and are underlying personal characteristics of an employee. An ability helps an employee to perform a certain task. This attribute is relatively enduring over the individual`s lifespan (Tippins and Hilton, 2010). Furthermore, the research subject is the monetary value of different facets of competencies in Research Paper 4. The O*NET items correlate with wages (Handel 2016) and, consequently, they are very suitable for this approach. Additionally, the results from the importance ratings are comparable over different countries (Taylor et al., 2008).

2.2 Learning, Forgetting, and Training

The goal is not to give a holistic overview of all the models in the field of operations research on the topic of workforce scheduling and learning, but to pick up some relevant topics from this area for this dissertation. Good overviews of workforce-scheduling models with multi-skilled workers, which incorporate learning, forgetting, and training are given by Van den Bergh et al. (2013) and De Bruecker et al. (2015). Simply by the number of articles in these reviews and the various possible solutions, one can see the importance of these models in the Operations Research (OR) literature of recent years.

Probably the first empirical confirmation of the learning curve effect in the context of industrial manufacturing comes from Wright (1936). He was able to show empirically, based on the construction of aircraft, that the average direct labor costs per aircraft (unit labor costs) fall with the number of machines produced (Wright, 1936). Since Wright's definition, learning curve research has proliferated and is used in a variety of contexts and use cases (e.g., Anzanello and Fogliatto 2011). Several articles explicitly address competency development in a quantitative model that includes learning, forgetting, and also training (e.g., Gutjahr et al. 2010; Heimerl and Kolisch 2010; Valeva et al. 2017).

Building competencies through learning helps employees to produce faster, at lower costs and with higher quality (Argote, 2013; Biskup, 2008). The literature distinguishes between induced and autonomous learning (or so-called learning-by-doing). Induced learning is triggered by training processes. Vice versa, learning-by-doing results from repeating comparable tasks (Adler and Clark, 1991; Biskup, 2008; Biskup and Simons, 2004). Training can help to reach higher competency levels faster. Furthermore, competencies which cannot be learned by learning-by-doing, due to a lack of opportunities to carry out the activity (e.g., because there is no demand for the product at the moment) can be acquired through training measures. Additionally, training measures can also help to prevent negative effects like forgetting (Jaber et al., 2003); however training measures are costly and the time spent on them cannot be used for productive production processes (Biskup, 2008; De Bruecker et al., 2015).

The aim of the models is often the simulation and optimization of learning and forgetting processes under certain restrictions or with different factors which have an influence on the system (Valeva et al., 2020). Valeva et al. (2017) have already investigated the interaction of volatility and capacity but only on three levels and without explicitly varying training measures. Additionally, in Research Papers 3 and 4 of this dissertation, the focus is on learning-by-doing, training, and forgetting. Therefore, it is important to focus on competencies which can be learned and trained but can also be forgotten (such as, for instance, skills). Some are enduring like personal traits or motivation (Spencer and Spencer, 1993). Therefore, competency development arises as an important question for companies. Competencies develop through learning and training. Contrarily, they decrease through forgetting or losing importance over time (Gutjahr et al., 2010). Consequently, total skill development is a combination of learning-by-doing, training, and forgetting. De Bruecker et al. (2015) show the development of skills, and thus learning, as having a positive impact on the employee's ability to perform a certain production task. In detail, they name the following factors to be affected positively by employee skills: processing time, production efficiency, product quality, and labor costs. Often, these models are applied to ramp-up scenarios. Terwiesch and Bohn (2001, p. 1) define ramp-up as the *"period between completion of development and full capacity utilization."* In this phase, learning of shop-floor employees is substantial for the success of a ramp-up in a production environment (Terwiesch and Bohn, 2001). During this time, employees gain more experience and increase their capacity utilization as well as flexibility (Hansen and Grunow, 2015; Qin et al., 2015; Terwiesch and Bohn, 2001). Skill-level targets, which avoid an undesirable behavior, are helpful for these models over several periods, as the periods end within the planning model. In real life, orders would still be expected to come in even after the ramp-up phase is over. Skill-level targets increase costs, but they are helpful to broaden skills within companies and to avoid unintended effects at the end of the planning horizon (Heimerl and Kolisch, 2010). There are a number of possibilities for which workforce-scheduling models that incorporate learning-by-doing, forgetting, or training, can be used. For instance, the simulation of different learning behaviors, which could hardly be analyzed in reality. In addition, there are a number of things that need to be taken into account by these models, e.g., the use of the above-mentioned skill-level targets at the end of the planning horizon. Therefore, it is advisable to use these mathematical models for the investigation of future demands on the world of work.

3 Selected Research Methodologies

The present dissertation uses different methods for data collection and generation as well as statistical analysis. In the following section, first the data collection or generation methods are presented and the choice of the applied method is explained. Afterwards, the methodological approach for the statistical analysis within the different research papers is reasoned.

3.1 Data Collection and Generation

Research Paper 1 is based on theoretical contributions from other authors. Regarding the potential changes to the workplace of the future through cyber-physical systems, and their consequences for the future workforce, several articles and studies already exist. Therefore, no further data were collected. Research Paper 1 contributes to the literature by connecting and evaluating various already published articles of other authors.

In Research Paper 2, a survey design was used for the monetary valuation of future work-related competencies. Furthermore, a measurement tool, based on a budget-allocation approach, was developed, implemented in a survey tool, and tested. Survey studies allow the efficient collection of data, within an acceptable time frame, to reach enough subjects who are belonging to the target group of the study and are willing to participate in the study (Eid et al., 2017; Jacob et al., 2013). The target group were HR and production managers from the mechanical and electrical engineering sector which were invited to participate in the study via email. It was important to get enough subjects from the target group to be able to make robust estimations of monetary valuations. The survey was programmed in Unipark (EFS Survey Software), a web-based survey tool for academic research. The main advantages are the numerous randomization options, reports and online statistics, the variable data export and the possibility to design pages flexibly using your own HTML code (Jacob et al., 2013), which also has been used to design the monetary valuation of the competencies. A further advantage compared to oral face-to-face surveys is that the effort is lower and also that no interviewers have to be trained (Eid et al., 2017; Jacob et al., 2013). Of course, qualitative studies in which data is generated by interviewing persons of interest also provide important insights about the monetary value of future work-related competencies. However, such studies are often limited by the number of interviews.

The competency descriptors were retrieved from the O*NET Database. These descriptors are well-established in practice as well as in academic research (Taylor et al. 2008; Handel 2016). Therefore, these are very suitable for the application in this study. For instance, they correlate with actual wages (Handel 2016) and the results of the importance ratings are comparable across different countries (Taylor et al., 2008). Although it is a hypothetical situation, several studies have already demonstrated that hypothetical surveys yield comparable results that are applicable to real-life situations (Mitchell and Carson, 2005).

For Research Paper 3 and 4, data sets from a simulation study were generated and analyzed. "Simulation modeling" refers to the development of mathematical models that replicate real-life systems in a simplified way. One advantage is the cost-effectiveness and the control of the experimental conditions. It is possible to show relations which would hardly be observable in real-life or which do not exist in reality. Moreover, it is always simplified and cannot represent the entire complexity of the real world. One main aim of simulations is to generate a better understanding of a real-life system and to obtain information about possible developments in reality that are useful for informed decision making in a complex and often dynamic system (Robinson 2014). As a basis for the simulation, a mixed-integer programming (MIP) workforce-scheduling optimization model within a computational study was used. Optimization models aim to find an optimal solution for a problem with a mathematical model which satisfy several constraints (Pachamanova and Fabozzi, 2010). In scheduling problems, limited resources (in this case, employees) are allocated to (production) activities over certain planning periods (Afshar-Nadjafi, 2021). MIPs are popular in operations research to optimize workforce-scheduling problems (Afshar-Nadjafi, 2021; De Bruecker et al., 2015; Van den Bergh et al., 2013), especially because they can be solved faster than non-linear programs (Cavagnini et al., 2020). Many models that deal with learning are non-linear (Anzanello and Fogliatto 2011; Cavagnini, Hewitt, and Maggioni 2020). Therefore, a linearization of the learning-curve with a step-wise function helps the model to be calculated in a reasonable time with acceptable gaps. Linearization or approximations are common for overcoming this problem (e.g., Olivella, Corominas, and Pastor 2013; Hewitt et al. 2015; Valeva et al. 2017). Within this model employees develop their competencies over several periods through learning-by-doing, forgetting, and training within a ramp-up scenario by performing different production activities. Thus, a system to demonstrate the competency development behavior was created. Within this mathematical model, 100 stages of demand volatility are simulated as an external influence factor. Furthermore, as a limiting factor, scenarios are built for three stages of employee capacity (low, medium, high) in all demand volatility stages. In the low-capacity scenario, employees do not have enough time capacity to meet the average demand for goods. Within the medium-capacity scenario, all demanded products can be produced in the respective period if there are no fluctuations in demand. In the high-capacity scenario, employees have enough capacity for production and for training on the side to prepare for periods of high demand. A skill-level target for the last period was also introduced to avoid an unnatural behavior at the end of the planning horizon. Within Research Paper 4, the simulation got an extension and, for example, budgeting and non-budgeting of training measures are included. In the non-budgeted scenario, the employees can train without restrictions over the whole ramp-up phase. In the budgeted scenario training is limited to the first five periods and the time capacity for training in these periods is limited.

The used workforce scheduling optimization models of Research Papers 3 and 4 were programmed using the General Algebraic Modeling System (GAMS) platform (Bussieck and Meeraus, 2004). Therefore, the state-of-the-art solver for mathematical programming, Gurobi 7.5.2, was used. Thus, near-optimal results were achieved for the individual simulation studies. These helps to obtain comparable results between the different scenarios in the simulation study.

3.2 Data Analysis

In Research Papers 2, 3, and 4, besides descriptive analysis, sophisticated statistical methods were applied. The data in Research Paper 2 were analyzed with linear mixed effects models (LMM), using the lme4 package (Bates et al. 2015) in the R environment (R Core Team 2016). These kinds of models are increasingly common in disciplines like biology, ecology (Harrison et al., 2018) or psychology (Magezi, 2015). Reasons are the flexible approach of these models with regard to complex-grouping and within-participant designs (Magezi 2015). For this type of statistical model, fixed and random factors/effects are modeled and statistically identified. Fixed factors estimate effects that are assumed to be constant across individuals using least squares. In the respective article these were, for instance, the competency categories, competency levels, the management function or control variables, such as age or gender. The allocated budget is the dependent variable. Random effects estimate variation across individuals in the dependent variable (i.e., at the population level) using shrinkage. This includes grouping variables (Magezi, 2015). In the employed statistical model, the random effect estimates the interrelated error terms due to individual participants' repeated responses.

For the statistical analysis of the simulation studies (Research Papers 3 and 4), generalized estimation equations (GEE) regression models within the platform R (R Core Team 2016) were used to test the formulated hypotheses and to obtain insights into the competency development behavior of the employees over several periods. This approach is widely used in the medical and life sciences such as epidemiology, and has its relevance for organizational research in addition to its use in political science or criminology (Ballinger, 2004). The GEE approach was specially developed by Liang and Zeger (1986) for the purpose of longitudinal studies, in order to produce more efficient and unbiased regression estimates particularly when data are not normal distributed (Ballinger, 2004). Therefore, this evaluation method is particularly suitable, as the learning behavior is analyzed over several periods. The analysis is performed by using the geepack package (Halekoh et al., 2006). GEEs are robust even when key assumptions are violated and they are an extension of generalized linear models (Liang and Zeger, 1986). Due to the time-dependent structure of our data, we used an autoregressive (AR-1) structure. Furthermore a Gaussian distribution and the identity link were chosen to correspond to a linear model (Ballinger, 2004). After the descriptive analysis in both simulation studies, we expected a nonlinear influence on the dependent variables by employee capacity; this was also confirmed by statistical analysis. This can be accounted for in a GEE analysis by adding a quadratic term to the given models (Twisk, 2013). Therefore, we extended the models by a quadratic term for the variable "capacity."

4 Contribution, Hypotheses, and Key Findings

This chapter summarizes the main contributions, hypotheses, and key findings of each Research Paper. As mentioned before, Research Papers 1 and 2 analyze which competencies are important and deal with how these can be described. Research Papers 3 and 4 deal with the development of competencies through learning and training, and how these are influenced by restrictions and volatility.

4.1 Summary and Key Findings of Research Paper 1

The manufacturing environment is changing extensively due to so-called megatrends and their change drivers. These megatrends and drivers are also changing the environment and the framework conditions for employees in the manufacturing industry. In particular, Industry 4.0 and cyber-physical systems are causing the world of work to change significantly, and routine work or tasks to be automated. When working with these technologies, employees have to deal with new technological and contextual complexities and to solve problems that they did not even know of their old working environment. This can lead to employees being overwhelmed and problems not being resolved. To survive in this turbulent environment, companies must synchronize their corporate competencies with the individual competencies of their employees (Reinhardt and North, 2003).

Research Paper 1 gives several contributions to the field of competency management, based or derived from existing literature, in order to help companies to adapt to the fast-changing new environment. First, it shows how competencies can be classified and categorized. A well-known approach is to categorize competencies as technical, methodological, social, or personal (e.g., Grote, Kauffeld, and Billich 2006; Meyer et al. 2015). Subsequently, expected changes in the world of work and, in particular, in the competency requirements of companies are presented based on the foreseeable technological changes, e.g., through cyber-physical systems. As the environment of manufacturing companies is changing, the role of the employees, the content of their tasks, and their duties are also changing. The automation of simple manufacturing processes and the activities that they include will increase the number of jobs with high complexity.

A classical scale to describe competencies (see North, Reinhardt, and Sieber-Suter 2013) was further evolved. The used scale contains the dimensions knowledge and experience, task complexity, autonomous work and self-management, and capability of reflection. For this purpose, evaluations can be made on three levels (connoisseur, experienced and advanced, expert). Each of these levels has an explicit description (anchors), and they are based on the experience of the respective employee. In addition, it is possible to further subdivide the individual levels. Similarly to the European language portfolio, the individual levels can then be further subdivided into 6 sublevels (A1, A2, B1, B2, C1, C2) (North et al., 2013). To adapt these scales in order to better capture the necessities for cyber-physical systems (as well as further technological changes in production), an extension was proposed. First, the task complexity was divided up. The automation of simple manufacturing processes and the activities they involve will increase the number of jobs with high complexity (Hecklau et al., 2016). Additionally, Kagermann et al. (2013) argue that cyber-physical systems create new forms of complexity. These new forms can be divided up into technological and contextual complexities. “Contextual complexity” can refer to the new and broader roles which jobs would require in future, i.e., when problems are unstructured or occur through information overload. Vice versa, “technological complexity” means the interaction characteristics of the technology (e.g., the usability of the interface) or the systems architecture (e.g., the variety of different systems) (Kölmel et al., 2014). Furthermore, the contextual complexity was divided into “structure of the task,” “content of the task,” and “interaction and collaboration.” These three factors are essential for the successful implementation of cyber-physical systems (Dworschak et al., 2013). Consequently, it makes sense for companies to include these dimensions in their competency evaluation systems.

4.2 Summary and Key Findings of Research Paper 2

Companies have to plan the selection of employees as well as the training measures for their employees carefully because both are time- and cost-intensive processes (Blatter et al., 2016; Seyda and Placke, 2017). In addition, companies should take into account that some competencies remain relatively stable over time. For example, abilities are less easy to train than technical or company-specific knowledge (Spencer and Spencer, 1993). At the same time, as already mentioned, the demands made on employees in manufacturing companies are changing significantly, as well as the tasks they will have to perform in the future and the way they will perform them (Bonin et al., 2015; Dworschak et al., 2013; Dworschak and Zaiser, 2014; Frey and Osborne, 2013). The consequences for companies from wrong investments in their workforce are also monetary. One reason is, for example, that companies are unable to provide certain services to customers because the companies do not have the necessary competencies. In part, it is also a case decision whether to invest in more competent employees when hiring and, where necessary, also to be prepared to pay a higher salary (Burrus et al., 2014) or whether to develop the own employees through training measures (Seyda and Placke, 2017). Nevertheless, the importance and the value of competencies needed in the future are often determined in scientific fields and in companies with the help of Likert scales only (e.g., Meyer, Brunig, and Nyhuis 2015) or with qualitative methods, such as the critical incident technique (e.g., Robinson et al. 2007). Only occasionally do scientists include the monetary value for competencies needed in the future (e.g., Humburg and van der Velden 2015; Vooren et al. 2019). This is an important basis for companies to make decisions about training measures or about hiring new employees, especially in light of the changes described above. Therefore, the first contribution of this particular Research Paper is a method for the monetary measurement of future competency requirements based on a budget-allocation approach. The measure gives competencies a monetary price tag in relation to other relevant competencies. Thus, this information can be used directly for decision-making about how much to invest in training measures or for hiring decisions.

The second contribution of Research Paper 2 is a case study on blue-collar workers and their required competencies for the future in order to master the challenges of Industry 4.0. Within this case study, 228 participants with relevant management positions in HR and production management valued competencies that had been pre-selected by industry experts. This shows, for a specific occupational group, which competencies will have a particular monetary value in the future. This group of blue-collar workers is particularly influenced by the new technologies in the field of Industry 4.0, and the importance of individual competencies will also change for this group (Haeffner and Panuwatwanich, 2018; Pfeiffer et al., 2016). Within this case study, a significantly higher willingness to allocate budget to several competencies was found.

First, experts choose 16 relevant competencies (KSAOs – four per category) from a pre-selection based on the descriptions of O*NET, according to their importance for the profession of mechatronics, especially with regard to Industry 4.0. Based on a realistically estimated budget, participants were then allowed to indicate, for the 16 selected competencies, how much the (additional) salary would be worth for a mechatronics technician. The experts value the particular competency at the minimal competency level and at the same time for the optimal level of the particular competency beyond the minimal competency level. Explanations for the zero ratings were further asked separately. For example, the competency could be a basic requirement for the job in the respective company or it could really have no additional value.

The highest valued category is "skills." It is mainly driven by the competencies complex problem-solving and troubleshooting. Surprisingly, despite its being often highlighted in the literature, "active learning" received the smallest share of the budget in the skills category. The second highest share of the budget went to the category "knowledge" and then to the category "ability." The valuation of "other characteristics" differs only slightly from the valuation of "knowledge."

Surprisingly, production managers value other characteristics more highly than HR managers do. Vice versa, HR managers give a higher share of the budget to the knowledge category than production managers do. This may be explained by the fact that production managers have a clearer perception of the challenges faced by mechatronics engineers in their day-to-day work, and therefore assess them differently than HR managers do. Probably, HR managers focus more on "obvious" competency categories.

4.3 Summary and Key Findings of Research Paper 3

In Research Paper 3, the impact from demand volatility and employee capacity on skill development is analyzed. To answer the research question of Research Paper 3, we developed a MIP workforce-scheduling model with learning-by-doing, forgetting, and training. Thereby, a data set with 300 scenarios was created, in which each scenario included 18 periods. The employee capacity is modeled on three stages (low, medium, high). Production is assumed to be without inventory, and it is not possible to produce goods in advance on stock and to satisfy demand in later periods. This omits a significant buffer for demand volatility.

In order to answer the research question, three groups of hypotheses were formulated. First, the simulated data provides evidence for the impact of volatility on the variables learning-by-doing, forgetting, and training. Demand volatility combined with limited capacity will make it impossible to meet the complete demand, and thus opportunities for learning-by-doing will be lost (H1a). Consequently, due to the lower production volume and the lost opportunities to learn, forgetting will also increase (H1b). On the other hand, employees can use periods of low demand for training. Therefore, as demand volatility increases, training intensity will increase to prepare for periods of higher demand (H1c).

Second, the impact of demand volatility on the achieved skills and efficiency gains is examined. Achieved skills are composed of learning-by-doing and training minus forgetting. They reflect the respective skill level of the employee in the respective period. Based on the first group of hypotheses, where learning-by-doing and forgetting have an overall negative effect with increasing volatility, it is expected that the compensation of positive effects from training is not sufficient (H2a) and achieved skills is negatively affected by demand volatility. Furthermore, efficiency gains are related to the achieved skills of the employee will also be negatively affected by demand volatility (H2b).

Within the third group of hypotheses, a focus is placed on the interactions between demand volatility and employee capacity and the impact on achieved skill levels and efficiency gains. Within these hypotheses, employee capacity is assumed to have a moderating influence on how demand volatility affects achieved skills and efficiency gains. With high capacity, the fluctuations are more likely to be balanced, with periods of low demand being used for training to prepare for periods of high demand. Therefore, both achieved skills and efficiency gains should increase with higher volatility and higher capacity, as employees are less disrupted by demand fluctuations. Table I–4 provides an overview of the formulated hypotheses in Research Paper 3.

The simulated data provide evidence for the impact of volatility on the variables "learning-by-doing," "training," and "forgetting" as well as "achieved skill units" and "efficiency gains." Furthermore, it shows the moderating effect of the different employee capacity levels on demand volatility. After the descriptive analysis, a nonlinear influence on the dependent variables from employee capacity was expected and a quadratic (squared) term for employee capacity was added to the existing models. The quadratic term was highly significant in all models. Consequently, the impact from employee capacity can be better described by a non-linear relationship.

Demand volatility impacts learning-by-doing negatively (H1a), as expected, and, vice versa, training positively (H1c). The effect of demand volatility on learning-by-doing disappears with high employee capacity and becomes non-significant. Forgetting (H1b) is positively affected by demand volatility. Furthermore, a higher employee capacity also leads to increased training behavior. In addition, the two outcome variables, achieved skills units and efficiency gains were analyzed; H2a is only partially supported. When analyzing the data, a U-shaped relation was found between demand volatility and employee capacity. Overall, demand volatility has a marginally positive but non-significant effect on achieved skills. Interestingly, opposing effects in the individual employee capacity scenarios were found. In the medium scenario, a negative effect of demand volatility on the level of achieved skill units, and in the low and high scenarios a positive effect on the reached level of achieved skill units, was found. Consequently, the direction of the impact here is strongly driven by employee capacity. Hence, it can be explained why demand volatility has a negative effect in the medium capacity scenario. When capacity is just high enough to meet average demand, volatility hits hard, and avoiding shortages becomes the top priority and targeted learning less important.

Table I–4: Hypotheses of Research Paper 3

Hypotheses			Evidence
H1	a.	Learning-by-doing is negatively affected by demand volatility.	supported
	b.	Forgetting is positively affected by demand volatility.	supported
	c.	Learning through training is positively affected by demand volatility.	supported
H2	a.	Achieved skills are negatively affected by demand volatility.	partially supported
	b.	Efficiency gains are negatively affected by demand volatility.	partially supported
H3	a.	Achieved skills are positively affected by the interaction of demand volatility and capacity, i.e., high-capacity levels allow the use of capacity for employee training.	supported
	b.	Efficiency gains are positively affected by the interaction of volatility and capacity.	supported

H2b is just partially supported. Through the non-linear relationship, again a contradictory impact was found. At least, the hypotheses for the interaction effects between demand volatility and capacity were supported. A positive impact from the interaction of these two variables on the achieved skill units (H3a) as well as on the efficiency gains (H3b) was found.

Overall, it must be stated that demand volatility leads to an unbalanced production program, and thus also has a strong influence on learning-by-doing and on forgetting (Shafer et al., 2001). Training helps to balance these effects, especially in periods of low demand, which also confirms the results of previous literature (e.g., Valeva, Hewitt, and Barrett 2017). Employees can acquire a higher level of competency in times of low demand in order to meet times of higher demand more efficiently. This is especially helpful for the achieved skill units and the efficiency gains when there is excess employee capacity for training in the early periods of a ramp-up. Furthermore, the analysis of the influence of demand volatility on achieved skills and efficiency gains revealed the moderating influence of employee capacity. In addition, effects from the interaction between demand volatility and employee capacity were found to have a significantly positive impact on the achieved skill units as well as on efficiency gains. On the one hand, this also shows how important it is to manage employee capacity, and on the other hand, it exhibits how training can help to prepare for periods of high demand during a ramp-up. It is important to notice that the three capacity scenarios seem to lead to different priorities. The low-capacity scenario is driven by reaching a skill-level target. Within the medium scenario, the main priority seems to be the avoidance of shortage costs, and in the high-capacity scenario, the main priority seems to be the decrease of production costs.

4.4 Summary and Key Findings of Research Paper 4

A typical case for new activities and changed processes are production ramp-ups. In production ramp-ups, it is also particularly important for companies to train their employees quickly and to integrate training measures into the ramp-up accordingly (Terwiesch and Bohn, 2001). Traditional training measures are normally limited in time and focused on the first periods of new production activities (Ally, 2009). This approach is no longer appropriate in times of volatile demand and constant availability of knowledge and training on new technologies. Therefore, we examine the impact of these measures in interaction with volatility and employee capacity.

For this purpose, the simulation of Research Paper 3 has been revised, improved, and 600 new scenarios with near optimal solutions have been calculated. Compared to Research Paper 3, adjustments were made for simplification of the mathematical model and for the different research objective. For example, the fact that several machines can also perform substituting activities has been omitted. Training opportunities are budgeted by two methods. On the one hand, the training capacity per period is limited. On the other hand, the time in which training can be utilized is limited to the early phase of the ramp-up and the overall possible time capacity for training is limited per period. In the other scenario, employees can train completely without restrictions across all time periods and the time budget is not limited. Within the hypotheses, the focus is on the total skill development, which consists of learning-by-doing, training, and forgetting. Table I–5 provides an overview of the formulated hypotheses in Research Paper 4.

Table I–5: Hypotheses of Research Paper 4

Hypotheses		Evidence
H1	The budgeting of training measures has a negative impact on skill development.	supported
H2	Demand volatility has a negative impact on skill development.	supported
H3	Employees' skill development is affected positively by the interaction effect of budgeting and employee capacity.	partially supported
H4	Employees' skill development is affected negatively by the interaction effect of budgeting and demand volatility.	supported

Hypothesis H1 is supported. The budgeting of training has a negative impact on skill development. Extensive training in the early periods can compensate for the effect of forgetting in the later periods, as a higher skill level is achieved from scratch. Especially in the low and medium employee capacity scenario, budgeting for training leads to low learning output, as there are logically fewer opportunities to learn in the first place. Consequently, a significant negative impact of budgeted training measures on skill development was found.

Hypothesis H2 is supported. A negative effect on skill development from demand volatility was found. This effect was confirmed in the low and medium scenarios. In the high employee-capacity scenario, the effect was positively significant. The individual effects of learning-by-doing, forgetting, and training are analyzed separately. Surprisingly, demand volatility impacts training positively. Forgetting is positively impacted by demand volatility. Whereby in the different scenarios, contradictory effects for forgetting occur. Demand volatility impacts learning-by-doing, as in Research Paper 3, negatively. In summary, this is plausible: In a scenario with high employee-capacity, demand volatility can easily be absorbed and training is also possible to prepare for times of higher demand. In scenarios with low-employee capacity, the system tries to avoid shortage costs.

Hypothesis H3 is partially supported. A positive significant impact from the interaction of budgeting and employee capacity was found for training and a lower significantly negative for learning-by-doing. Nevertheless, the effect from training overweighs and the learning output is also positively significant. It is certainly advantageous that, especially in the case of high employee capacity, training can also be used more intensively in the first periods without producing shortage in the budgeted scenario. Therefore, this effect is understandable. So, in the budgeted scenario, employees are trained on a higher skill level in the first periods when capacity is available. Consequently, through a higher achieved skill level from training in the first periods, forgetting increases significantly in this case, but the effects from training overweigh. Overall, the impact on total skill development is positive but not significant due to these counteracting effects. Therefore, this hypothesis is only partially supported.

Hypothesis H4 is supported. There is a negative impact from the interaction between demand volatility and the budgeting of training on the total skill development of employees. One reason for less training is certainly the shortage costs that would otherwise arise if employees were trained instead of working in the production processes. Moreover, in the budgeted scenario, it is not possible to catch up with training if the demand is high in the first periods. The budgeting of training measures has a negative impact on skill development; especially when low employee capacity is available, the effect is stronger. Consequently, the flexibilization of training measures can be helpful for companies.

5 Conclusions

In this final chapter of the introduction to this thesis, a summary of the key findings and the theoretical as well as managerial implications is presented. Finally, the limitations of the single Research Papers and the overall limitations of this thesis are shown. An outlook for possible future research contributions, which can build on the dissertation, is presented here.

5.1 Summary of Key Findings

The present dissertation aims at giving several contributions to the field of competency management in manufacturing companies. For that purpose, Research Papers 1 and 2 focus (Strand 1) on the measurement and which facets of competencies need to be measured in order to determine the future needs of companies and also of employees. The second strand focuses in particular on competency development within ramp-up scenarios. To accomplish this, Research Papers 3 and 4 examine the influence of the interaction between demand volatility, employee capacity constraints, and the budgeting of training measures on the development of competencies in simulations. Table I–6 shows the research contribution / research question of each article and gives an overview of the key findings of each Research Paper.

Table I–6: Summary of Key Findings / Contributions of the Research Papers

Research Paper	Research Question / Contribution	Key Findings / Contributions
RP 1	Presentation of impacts on competency management through cyber-physical systems and how this influence can be represented in a rating instrument.	▪ Changing roles of employees, content of tasks, and increasing technological and contextual complexity create new needs for competency evaluation ▪ Proposals for the extension of a well-known competency rating instrument to better meet the challenges posed by cyber-physical systems.
RP 2	A novel monetary-based measurement method to determine the value of future work-related competencies. A case study on blue-collar workers, particularly from mechatronics, to identify their required competencies for the digital age.	▪ An intuitive assessment method has been developed, which, based on a budgeting approach, puts a large group of competencies in relation to each other and does so at two competency levels for monetary valuation of competencies ▪ The skills category has the highest value. Knowledge is also considered to be very valuable. Within the category skills, complex-problem solving in particular is seen as very valuable. ▪ Different disciplines value competency categories differently. Here, for example, HR managers rate knowledge higher than production managers do.
RP 3	What is the impact of demand volatility and its interplay with employee capacity on the learning and training of employees in production ramp-ups?	▪ Demand volatility has a negative impact on skill development. ▪ The capacity scenarios determine the priorities of the system and the learning strategy (skill-target vs. avoiding shortages vs. minimizing cost). ▪ The interplay between demand volatility and employee capacity should be considered within learning strategies. Surprisingly, a non-linear relationship between these two factors was found.
RP 4	What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems?	▪ The budgeting of training has a negative impact on skill development. ▪ Demand volatility has a negative impact on skill development. ▪ A positive significant impact from the interaction between budgeting and employee capacity was not found for total skill development through counteraction effects from the other variables. ▪ There is a negative impact from the interaction between demand volatility and the budgeting of training on the total skill development of employees.

5.2 Theoretical Contributions and Managerial Implications

The results of this dissertation have practical importance beyond their contribution to the theoretical understanding of competency management in dynamic and turbulent environments. Within the dissertation, different aspects of competencies, competency ratings, and valuation as well as competency development under distinct influencing and limiting factors are addressed, by different methodological approaches.

The research on competencies, their classification, their development, as well as their evaluation will gain even more importance in the up-coming years, due to the transformations in the production world. Industry 4.0, an aging society, and other megatrends are strong drivers here. In particular, however, the transformation (through digitization) within production will tremendously change the world of work and the needs of employees and employers. Managers should take into account which competencies will be important for their companies in the future, as well as what value these competencies have for the company. Furthermore, they should consider which competencies can be developed with a potential candidate, which ones may need to be promoted through internal or external training, and which ones they need to purchase and assess accordingly. The case study used in Research Paper 2 shows that competencies such as complex problem-solving skills have a higher value for managers during the hiring process. Technological complexity can be partially offset by learning new traditional skills. However, increasing contextual complexity becomes particularly relevant for tasks that require more social and personal competencies, which are enduring and difficult to learn.

It is not only the world of work that is changing, but also the way that we acquire competencies. The constant availability of knowledge (through the internet, digital libraries, smart glasses, etc.) can also cushion negative effects, e.g., demand volatility, as shown in Research Paper 4. However, employees must then also have the ability to acquire and process this knowledge. According to Spencer and Spencer (1993), several more soft competencies in particular cannot be acquired as easily as knowledge. Companies must therefore make sure that suitable candidates already have these competencies or consider how the relevant employees can acquire them. Thus, in addition to the evaluation of various qualitative criteria of competencies, a monetary evaluation of competencies, as shown in Research Paper 2, is also an important and simple benchmark for decisions in training or hiring that should be applied.

Managers should take the effects from learning, training, and forgetting into account when they plan their staff along with the environmental dynamics and restrictions. It is especially important to manage employee capacity. In Research Paper 3, it is made obvious how different priorities (e.g., skill level target vs. avoiding shortages vs. reduction of production costs) can influence the learning behavior and how this prioritization is moderated by employee capacity. Additionally, demand volatility has a strong impact on learning behavior.

Furthermore, training can help increase the efficiency of the given employee capacity. On the other hand, training of competencies can help to prepare for turbulences from the environment. Consequently, managers should set their priorities and adapt their training programs according to their environment, their capacity, and their priorities. Training and hiring are expensive processes in employee capacity. Therefore, these are investment decisions of companies. What is the benefit of investing in training compared to the longer search for suitable candidates or possibly not being able to accept an order due to a lack of personnel resources? The question on how to design training programs has been partially answered by Research Paper 4. Traditional training approaches are limited to a certain period and also restricted in the time budget. The consequence is that the employees are not available during this period even if work is available. In contrast, permanently available, e.g., digital, training programs could remedy this situation. The potential and design of constantly available digital work instructions in production environments has already been analyzed and discussed by Letmathe and Rößler (2021). Overall, it is important to notice that the budgeting of training measures has a negative impact on skill development. A further reason is that constantly available training helps to avoid forgetting.

At this point, Research Paper 2 also provides valuable contributions. Knowledge and skills, which are more learnable than e.g., abilities or personal characteristics, are highly valued by HR and production managers when hiring a candidate. These kinds of competencies can be better acquired through learning-by-doing or through suitable training. Candidates do not necessarily have to already be trained in these competencies when they are hired by companies. Of course, this also depends on the tasks and the respective required competencies within the companies. Nevertheless, managers should integrate the value of different competencies in their considerations when they plan training measures for their current employees or hiring new employees. First, this valuation can assist companies to get a monetary orientation for competency-based employee selection. Second, companies can include these considerations when weighing up whether or not to invest in training. Third, companies can rethink their wage offers. Companies can save themselves money and cover their competency requirements of the future in a more targeted way if they already plan what the competencies are worth to them during the personnel selection process. This requires a monetary assessment of the competencies and can also reveal conflicting objectives between different assessments, as can be seen, for example, in the different assessments by HR managers and production managers for the category “knowledge.”

5.3 Limitations and Further Research

This dissertation brings together several issues in the context of learning and competency management within the manufacturing environment. Several relevant topics for managers and scientists are addressed. Clearly, not all issues in this area can be exhaustively addressed. There are some limitations, which, however, also offer the opportunity for further research in this area. First, each individual Research Paper has limitations that can be listed and that are stated in the respective article in more detail.

The simulations in Research Papers 3 and 4 are based on fictitious and simulated data and show only a possible behavior. Even if the data are inspired by real situations, they were consciously set by the researchers. Furthermore, the parameter countereffects from reality are not included. For future research, it would be even more promising to empirically investigate budgeting and allocation procedures for learning and training. Additionally, it would be helpful to use empirical data for the simulation. For the practical data of the simulation, heuristics should be used, if necessary, to reduce the computation time. Furthermore, in both simulation articles, a restricted number of employees and activities are used. This could be expanded. The strong influence of employee capacity and the interplay with other factors should be analyzed deeper. In addition, several more stages or a flexibilization of capacity could be an interesting extension in order to understand these effects even better, especially the found non-linear relationship.

Demand volatility was used here as an example of turbulences which occur through changes in the environment of the companies. Employee capacity and budgeting of training measures were used for restrictions. More turbulences and their interaction should be tested here. Known turbulences are, e.g., complexity, uncertainty, and ambiguity. In combination with volatility, these phenomena are often prominently mentioned in the literature and in practice as “VUCA” (Bennett and Lemoine, 2014a, 2014b). After these phenomena have often been considered in isolation in science, a holistic view would be useful (Millar et al., 2018) to learn more about the impact on competency development.

Due to the novelty of many topics, such as Industry 4.0, not even the terms have been clarified conclusively. This also applies to “competency management.” Despite the fact that this dissertation makes a contribution to the competency management in manufacturing companies, there are still many open research gaps in this field. Especially due to the dynamics of external influences, it will be necessary to continue to make contributions in this area.

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II Research Paper 1: Competence Management in the Age of Cyber-Physical Systems

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Abstract: To maintain industrial competitiveness in times of Cyber Physical Systems (CPS), organizations need to invest in sets of individual competencies. We show how competence management can synchronize individual and organizational competencies. We categorize different types of competencies which enable firms to master the technological and contextual complexity of CPS. Furthermore, we introduce a measurement instrument for these competencies, which includes aspects of technological and contextual complexity.

1 Companies in the Age of Industrie 4.0

Production in high-wage countries is being increasingly influenced by an aging workforce and the explosion of knowledge (Abele and Reinhart, 2011; DeLong, 2007). As this aging workforce retires, knowledge will also leave the companies (Calo, 2008). Furthermore, a higher number of more complex products, new production processes, growing competition through internationalization, and especially new technologies in markets with rapidly changing conditions are a tremendous challenge for companies. To maintain their competitiveness in dynamic and turbulent environments, it is important for companies to anticipate and address these changes (Cao and Zhang, 2008). Otherwise, these turbulences will lead to a range of problems for companies such as reduced levels of service or higher inventory costs (Kulp et al., 2004). Scientists and practitioners alike argue that the respective technological changes will lead to the fourth industrial revolution (Bauernhansl, 2014; Becker, 2015; Kagermann et al., 2013; Monostori, 2014). According to Broy, nothing has changed our lives as much over the last 40 years as the digital revolution (Broy, 2010). Ongoing digitalization will enable firms to connect machines, storages and operating materials along their entire value chain. These underlying systems are called cyber-physical Systems (CPS). In this context, the term 'Industrie 4.0' has become popular in Germany (Hirsch-Kreinsen, 2015). The core element of Industrie 4.0 is the vision of the smart factory that enables the use of the internet's intelligence for planning and executing production and increasing the agility of production systems (Becker, 2015; Kagermann et al., 2013). The human element is embedded in these systems as an actor (managing tasks), a problem solver and a collaborator (Bochum, 2015; Gorecky et al., 2014; Hirsch-Kreinsen, 2015).

It is obvious that the related technologies will lead to significant economic and social changes (Evangelista et al., 2014). CPS can help to address key challenges related to an aging workforce or to scarce resources, but they also create a new form of complexity for the manufacturing industry (Kagermann et al., 2013). Consequently, enterprises have to deal with this growing complexity and with the requirements of faster innovations and flexibility. One key factor for meeting these challenges will be to invest in employee competencies (Spath et al., 2013).

To fully utilize the potential of digitalization, companies will have to find the right balance between technology and human factors (Dworschak and Zaiser, 2014). The traditional world of work has not prepared the workforce for the often demanding tasks of CPS. To achieve a good match with the technological challenges and complexity, firms need more long-term investments in the workforce (e.g., hiring and qualification) (Francalanci and Galal, 1998; Piliouras et al., 2014). Kölmel et al. (2014) distinguish between technological complexity and contextual complexity, both rising due to the introduction of CPS. Technological complexity either refers to the fundamental interaction characteristics (input and output) of a technology, or to the fact that the underlying system architecture is complex, linking a variety of different systems, architectures, agents, databases, or devices. Contextual complexity includes the broader tasks, roles, or jobs that the technology is supposed to support, especially when tasks are open-ended or unstructured (Kölmel et al., 2014). To handle these complexities, the development of technical as well as contextual competencies is crucial for the interaction between humans and technological systems (acatech, 2011). Baxter and Sommerville (2011) highlight that the failure to incorporate socio-technical approaches, which take necessary human competencies into account, tends to result in ill-defined requirements as well as poor system design, system delays and unmatched expectations (Baxter and Sommerville, 2011). Consequently, due to demographic factors (e.g., an aging workforce) and the more demanding skill requirements of CPS, companies need to maintain and develop the competencies of their workforce (Plattform Industrie 4.0, 2014) in the areas of technological knowledge and contextual complexity.

To synchronize organizational and individual skills, it is important to analyze the required competencies for CPS and the actual individual competencies of the employees. The development of such competencies is time-consuming and costly. Hence, workforce management approaches should focus on the early identification and evaluation of competencies, which are relevant for the enterprise's strategy and for dealing with technological change. The identification of competence gaps and the planning of workforce requirements (hiring and qualification of employees) will become even more important in the future (Becker, 2015; Meyer et al., 2015). Traditionally, such competencies are often clustered into technical, methodological, social, and personal competencies (Grote et al., 2006; Meyer et al., 2015). Technical and methodological competencies will play an important role in handling technological complexity. Furthermore, social and personal competencies are crucial to handle the contextual complexity of CPS (Dworschak and Zaiser, 2014). As employees will not be able to solve all problems individually, collaborative problem-solving capabilities will be even more important (Biesma et al., 2007; Bonin et al., 2015; Dworschak and Zaiser, 2014)).

In our article, we categorize different types of influences on these critical competencies in the future to master the technological and contextual complexity of CPS. Furthermore, we introduce a short measurement instrument for these competencies that also includes aspects of technological and contextual complexity.

2 Cyber Physical Systems

According to Lee (2008), "*Cyber-Physical Systems (CPS) are integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa*" (Lee, 2008; 1). CPS include embedded systems and devices. These could be, for example buildings, transport and medical devices as well as logistics, coordination and management processes or web services. Sensor systems collect data from physical systems and actors. Based on the evaluation and storage of data, CPS act or respond to the physical world with which they are connected locally or globally. Furthermore, they use data that are available worldwide and they have some multimodal human-computer interfaces (Broy and Geisberger, 2012). Figure II–1 illustrates a typical CPS architecture.

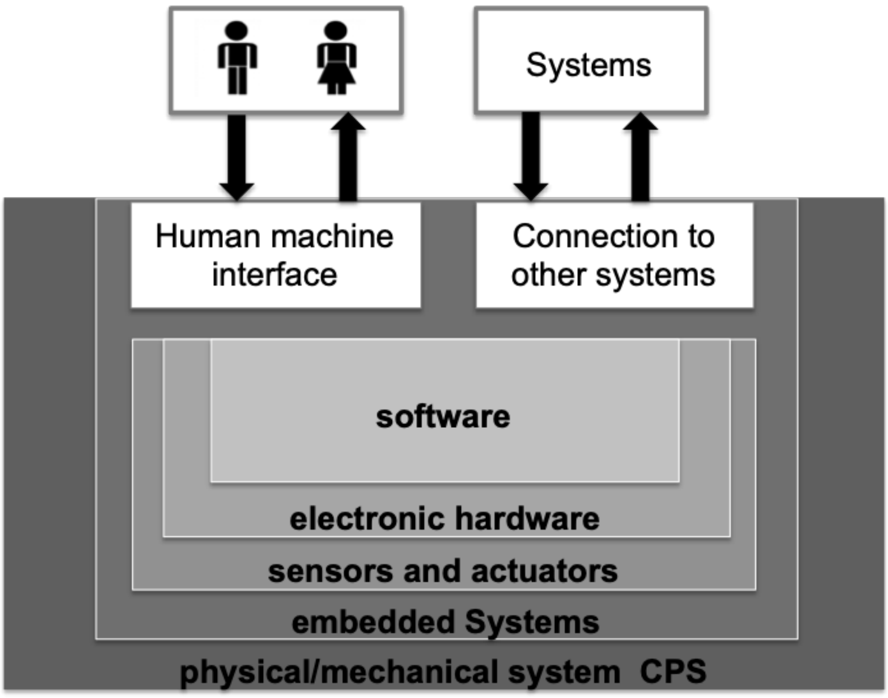

Figure II–1: CPS Architecture[1]

Applications of CPS have enormous potential. They can be applied in medical devices and systems, for traffic control and safety, in automotive systems, for process control, for energy

[1] Brettel et al., 2014; Broy and Geisberger, 2012.

conservation, in environmental control, in avionics, for the control of critical infrastructures (e.g., electric power), in defense systems and in manufacturing, etc. For example, they can improve the efficiency and safety in transportation systems by connecting cars and smart traffic data systems, resulting in reduced fossil fuels consumption and lower greenhouse gas emissions (Lee, 2007).

With the objective of improving the productivity, the quality and the stability of production systems, manufacturing can be positively influenced by so called cyber-physical production systems (CPPS) (Ittermann and Niehaus, 2015; Monostori, 2014) .Therefore, the introduction of CPS is a widely discussed topic, because CPS are expected to change business models and entire market structures (acatech, 2011). According to Schlick et al. (2012), the main characteristics of the change in production will be: smart objects, comprehensive networking, the use of internet standards for communication, adaptive and agile production systems, vertical integration in the network and the changed role of employees. The technological changes generate new opportunities for collaborative value creation, such as the potential to utilize the customer knowledge for the development and production processes (Wulfsberg et al., 2011). Owing to the opportunity to exchange information worldwide, labor becomes more independent from the locations of the manufacturing sites (Krenz et al., 2012).

CPS has to be resilient and adaptable to unpredictable and also adverse events. Not every component is reliable (Lee, 2007). The design and use of CPS is a considerable challenge involving specific requirements such as safety, usability or trust in the system (Kölmel et al., 2014; Lee, 2008). The introduction of CPS does not just concern technological change: it will also alter the role of employees, their collaboration and workplaces. Especially the human-machine interaction will require substantially different competence profiles of many employees. To address all these changes, the working group Industrie 4.0 has defined key priority areas with a need for business action or industrial policy for introducing CPS (Kagermann et al., 2013):

- Standardization and open standards for a reference architecture: Information will be exchanged within and between companies. For a collaborative partnership, it is necessary to develop common standards. Furthermore, a reference architecture with a technical description would be helpful for implementing these standards.
- Managing complex systems: Trends, such as product customization, market requirements and increasing functionalities in complex production networks, are increasing production complexity. Explanatory and planning models can help to manage this complexity.
- Broadband infrastructure for industry: Existing communications networks have to be extended

to meet the requirements of higher volumes and a better quality of data exchange.

- Safety and security as critical factors for the success of Industrie 4.0: The planned data and knowledge, which should be exchanged between companies or manufacturing facilities, have to be protected (security). Furthermore, the CPS (machines, products etc.) should not be a danger to employees or to customers (safety). Hence, CPS needs to be protected against misuse and unauthorized access.
- Work organization and work design in the digital industrial age: Industrie 4.0 will change the content of work processes and the role of employees. One reason for this is real-time-oriented control. Employees will be more involved with ad hoc problem solving instead of routine tasks. They will be more responsible for ensuring CPS stability and maintenance than for performing object-oriented tasks such as working on a part or a product. Furthermore, work design will be more participative and there will be a need for lifelong learning.
- Training and professional development for Industrie 4.0: Job and skill profiles will change through modified technological, social and organizational contexts. Current standardized training programs are limited and it will be a challenge to identify the relevant training contents. It is likely that interdisciplinary orientation and new qualifications will gain tremendous importance.
- Regulatory framework: The new complexity of digitalization cannot be mastered through existing regulatory frameworks. Modified regulatory frameworks will have to fulfill certain requirements, such as data protection, and should have the flexibility to utilize the potential benefits of new and rapidly changing technologies.
- Resource efficiency: One of the major goals of CPS implementation is to increase the productivity of production systems, i.e., to increase the ratio of output and resources, such as raw materials, energy, human and financial resources.

3 Competencies and Competence Management

This section discusses competence management as the basis of managing employees in the digitalized world. We distinguish between organizational and individual competencies and provide a short example of how the respective competencies can be classified and measured.

3.1 Defining Individual and Organizational Competencies

Technological inventions in the context of CPS are changing the avenues to competitive success and require the effective management of knowledge and employee skills (Sanchez, 2001). But there are more than just knowledge and skills involved. McClelland (1973) showed that conventional knowledge or ability tests cannot predict whether people can cope with the tasks of their jobs and he argues in favor of a behavioral and task-oriented analysis of competencies (McClelland, 1973). Competencies cannot be documented by certificates. Competencies are always related by actions in different situations (Kauffeld, 2006). However, there is no universally accepted definition of competencies. Reinhardt and North (2003; 1374) argue that *"A person's competence basically describes a relation between requirements placed on a person/group or self-created requirements and these persons' skills and potentials to be able to meet these requirements. Competencies are concretized at the moment knowledge is applied and become measurable in the achieved result of the actions."* They regard competencies as being embodied in applied knowledge and measurable from the results of given tasks. This conforms with (Sanchez 2001; 7), who stated that "*skills are the abilities an individual has to do things. Competency is the set of skills that an individual can use in doing a given task.*" According to Erpenbeck and von Rosenstiel (2007; XIX), competencies are "*dispositions for self-organization activities*". Hence, competencies relate to problem-solving abilities, whereas it is possible to test qualifications in exams with always the same requirements. While test results reflect actual knowledge, they do not demonstrate whether somebody has the ability to transform this knowledge into sufficient action. In this sense, qualifications are dispositions of knowledge and skills (Erpenbeck and von Rosenstiel, 2007).

The sum of all skills or abilities which an individual has and can use to fulfill tasks is the so called 'competence portfolio' of an individual. According to (Reinhardt and North (2003) the competence portfolio of an individual and that of an organization should be synchronized. Furthermore, there is a divided view of competence management. On the one hand, competence management is seen as a part of organizational science (North, 2011). On the other hand, competence management is regarded as belonging to cognitive science (Erpenbeck and Heyse, 2007; Reinhardt and North, 2003).

In the context of organizational competencies, it is possible to distinguish between capabilities and competencies. Prahalad and Hamel (1990, 82) summarize core competencies as "*the collective learning in the organization."* According to them, knowledge consists, for example of the skills in production or in technologies, or a combination of both. In contrast, capabilities are based more on (cross-functional) processes or routines within the business (Prahalad and Hamel, 1990). Both competencies and capabilities are strategically relevant resources (Marino, 1996). Organizational capabilities and competencies can be an important competitive advantage if they are costly, rare and valuable resources (Barney, 1995).

North et al. (2013) argue that competence management should be aligned with the technology, the processes and the information technology infrastructure. Hence, it is important to differentiate between organizational competencies and individual competencies and to define those individual competencies that employees have to acquire to fulfill organizational requirements.

Reinhardt and North (2003) call this 'competence adaptation'. The development of individual competencies should focus on the most relevant competencies/capabilities for successfully implementing the organization's routines and processes, such as knowledge in software engineering for embedded systems. Moreover, competence management should be aligned with the strategic and market decisions and the organizational structure. Reinhardt and North (2003) already developed a model for matching organizational and individual perspectives. As discussed, companies have to achieve a fit between technologies – in this case the technology of CPS – and the competencies of humans. For this purpose, it is also important to describe and classify competencies from an organizational point of view in order to meet these requirements. Hafkesbrink and Schroll (2010) describe organizational competencies for open innovation as the organizational readiness, the collaborative capability and the absorptive capacity. They argue that these organizational competencies can only be met by bundles of individual competencies enabling organizational members to collaboratively perform tasks with a low initial structure. Such collaborative competencies help to develop the absorptive capacities of the whole organization (Hafkesbrink and Schroll, 2010).

3.2 Classification and Measuring of Competencies

In the first part of this section, we discuss classifications of individual competencies. Then we go on to suggest a method for measuring competencies based on previous literature in this field.

Competence classification

Stoof et al. (2002) define five possible features of competence, which can be analyzed by answering the following five questions: 1. Is it a personal characteristic or is it a task-specific characteristic? 2. Is it the competence of an individual person or is it the competence of a team or an entire organization? 3. Is it a specific competence with a clearly defined scope that is not useful for other tasks, or is it a general competence with a broader scope within a profession or covering more than one profession? 4. Do different levels of a given competence exist or does a different level define a new competence? 5. Can the competence be taught, like knowledge, or can it not be taught?

Often competencies are divided into 'hard skills' (e.g., technical competencies) and 'soft skills' (e.g., communication competencies). There are already several classifications that have been developed for competencies to describe and distinguish them (Erpenbeck and von

Rosenstiel, 2007; North et al., 2013). According to Reinhardt and North (2003) the portfolio of individual competencies can be divided into professional, methodological and social competencies. Crawford (2005) elaborated a comprehensive approach to describe, categorize, identify and measure competence against standards for project management (see Figure II–2). She defines three categories: Input competencies, personal competencies and output competencies. Input competencies consist of knowledge and skills. Personal competencies are personality traits, attitudes and behaviors. Output competencies can be shown by demonstrative performance measures through a company's diagnostic systems (Simons, 2000).

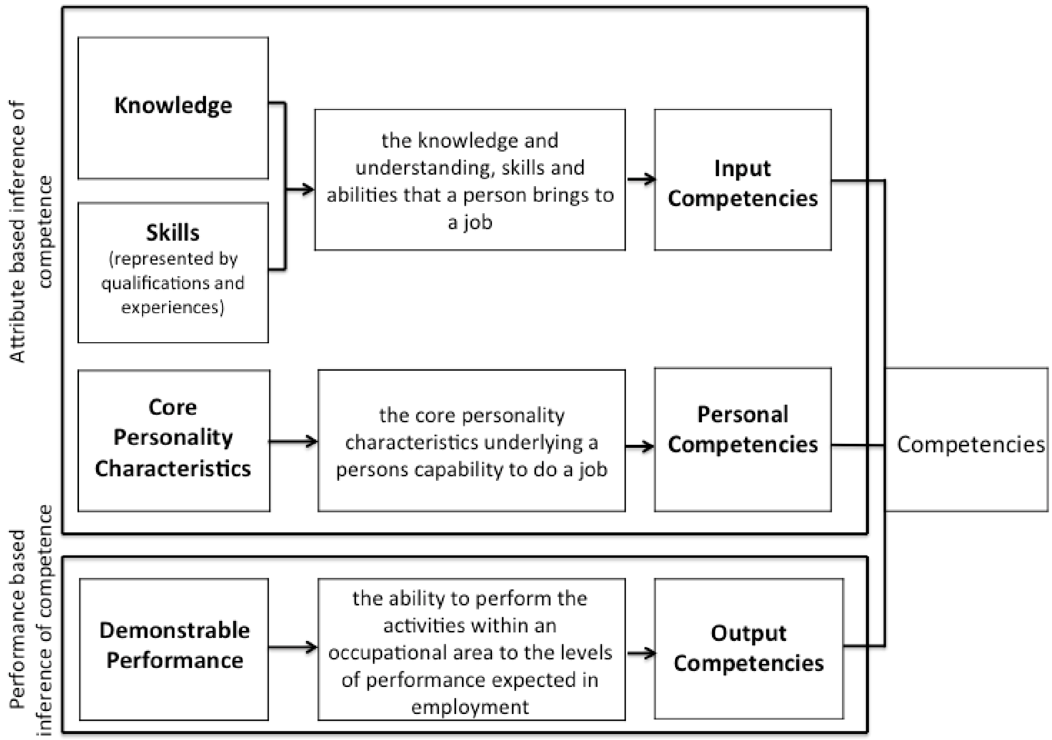

Figure II–2: Integrated Model of Competence Identifying Components of the Overall Construct[2]

Erpenbeck and von Rosenstiel (2007) use four categories to describe competencies: methodological and professional competencies, personal competencies (willingness to learn), activity-and action-oriented competencies (e.g., flexibility) and socio-communicative competencies (e.g., team skills). We adopt a well-established approach (Gerst, 2015; Grote et al., 2006; Hafkesbrink and Schroll, 2010; Kauffeld, 2006; Meyer et al., 2015) that distinguishes between functional (technical and – in parts – methodological) and cross-functional (social, self-management and – in parts – methodological skills) competencies. Technical competencies

[2] Crawford, 2005.

are knowledge, skills or experience, which are applicable in specific technical contexts. Methodological competencies encompass the application of teachable and well-defined methods, for instance, heuristic methods for solving complex problems. Social competencies reflect the ability to work successfully in teams and in cross-functional processes. Self-management competencies or personal competencies, on the other hand, help individuals to organize themselves efficiently, for example through self-control, self-organization and motivational competencies, such as the willingness to learn (Gerst, 2015; Grote et al., 2006; Kauffeld, 2006; Meyer et al., 2015) (see Figure II–3).

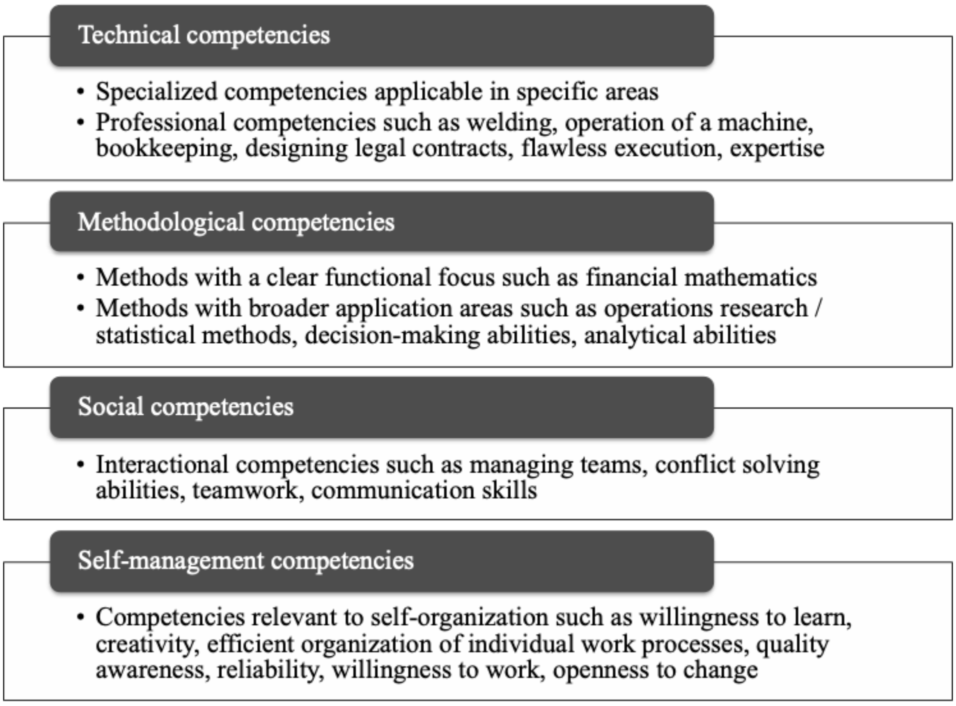

Figure II–3: Competence Classification[3]

Competence measurement

Although a widely accepted method for measuring competencies does not exist, several approaches for measuring competencies, e.g. with qualitative or quantitative analysis, have been suggested (Erpenbeck and von Rosenstiel, 2007; North et al., 2013). These present a large overview of different competence measurement approaches with a focus on self-organization disposition from the German-speaking research community (Erpenbeck and von Rosenstiel, 2007).

Learning from experience is particularly important for expanding necessary knowledge. For example, Barr et al. (1992) and Pennings et al. (1994) showed positive correlations between

[3] based on: Grote et al., 2006; Kauffeld, 2006; Meyer et al., 2015.

learning from experience and the success and renewal of a firm. Therefore, focusing on experience as an indicator of competence in a given field can be beneficial for the evaluation of competencies in different dimensions. For the dimension of competencies, we adopt the proposal by North et al. (2013), which can be adapted to different contexts. They propose four simple dimensions for the assessment of competencies: knowledge and experience, complexity of the task, autonomous working and self-management and reflection capability. These four dimensions are used to grade the competencies of an employee. Furthermore, they use a well-tested scale for the classification of three steps: connoisseur, experienced/advanced, and expert. Table II–1 illustrates the described framework for the experience-based evaluation of competencies in their different dimensions. The scale used relates to the European Language Portfolio proficiency levels (A1-C2) and is built on the four assessment dimensions shown above. These proficiency levels can be subdivided into six steps, comparable to the European Language Portfolio. By using this scale it is possible to attribute a qualitative disposition to a competence (North et al., 2013).

Table II–1: Evaluation of Competencies[4]

Dimensions	Connoisseur		Experienced and advanced		Expert (can train others)	
	A1	A2	B1	B2	C1	C2
Knowledge and experience	"What level of knowledge and what degree of experience are required in a specific field? Basic knowledge, differentiated areas of expertise or comprehensive knowledge with varied application experience?"					
Task complexity	"The degree of complexity depends on how many relevant factors exist and the mutual dependencies between these factors."					
Autonomous work and self-management	"The path, the goal and the willingness to fulfill the task are the three key aspects of this evaluation dimension."					
Capability of reflection	"Competence means always reflecting on your own actions or the actions of others in the context of a situation. To what extent am I capable of critically reflecting on processes, situations, people and behavior as to whether they meet the expected requirements?"					

4 Consequences and New Competence Requirements for Employees through CPS Complexity

The consequences of introducing CPS are being widely discussed but are mostly based on speculation. One exception is the study by Frey and Osborne (2013), which received a great deal of attention. According to Frey and Osborne (2013), 47 percent of the jobs in the US have a high risk of being automated over the next ten to twenty years. Furthermore, the probability of automation declines in line with the level of salary and education of the employee. Bonin et al. (2015) conducted a similar study for Germany on a more detailed level for different types of tasks. They found that only twelve percent of current job tasks in Germany and nine percent of those in the US have a high probability of being automated over the course of the coming years. However, according to these studies, the nature of existing tasks will shift in focus and towards a higher degree of complexity. In this context Kölmel et al. (2014) distinguish between

[4] based on: North et al., 2013; 70-71.

technical complexity and contextual complexity (see Table II–2). Technical complexity refers to the interaction characteristics and the architecture or databases of the system (Golightly et al., 2011). Contextual complexity particularly refers to a change in the nature of existing tasks. Tasks performed by humans will become more unstructured and employees will have to perform a wider range of tasks, with their roles changing towards problem solving and collaborative work. Competencies such as obtaining sufficient information and interpreting data correctly will become more important. Routine tasks with clearly defined steps and results will become increasingly more automated (Bonin et al., 2015; Dworschak and Zaiser, 2014; Frey and Osborne, 2013).

Table II–2: Technical and Contextual Complexity of CPS Task Characteristics[5]

	Technological Complexity	**Contextual Complexity**
Increasing challenges of CPS for the workforce	▪ Interaction characteristics technology (interfaces, coordination, information exchange, systems stability) ▪ Systems architecture and variety of different systems, agents, architectures, devices, or databases	▪ Broader tasks, roles or jobs ▪ Open-ended and unstructured tasks (problems) ▪ Less structure ▪ Abstractness ▪ Interpretation and use of information ▪ Collaboration ▪ Information overload

As a result of automation, it is not sufficient to train routine tasks and to develop all necessary competencies. Employees also have to make interventions if unexpected and complex non-routine problems occur (Windelband et al., 2013). (Gorecky et al. (2014) also see the primary task in setting and supervising the realization of the production strategy for a set of production facilities. In these views, humans are acting as creative problem solvers for complex problems or opening up new optimization potentials. According to Mccreery and Krajewski (1999), complex tasks are associated with slow learning and fast forgetting and simple tasks with fast learning and slow forgetting. Therefore, companies have to identify and develop the appropriate combination of competencies and in particular the methodological knowledge that is required to analyze and solve problems. Moreover, self-management competencies will become crucial for employee performance, whereby employees will have to learn how to obtain the necessary knowledge and information (Windelband et al., 2013). Following this view of complexity, three factors will gain key importance for the successful implementation of CPS that will also influence the contextual complexity:

[5] based on: Frey and Osborne 2013; Dworschak and Zaiser 2014; Bonin et al. 2015.

- The role of employees
- The content of the task
- The interaction and collaboration of humans with systems and within work teams

The role of employees: Windelband et al. (2013) analyzed the future skill requirements in the field of logistics and developed two possible scenarios (see Table II–3) (Dworschak and Zaiser, 2014; Windelband et al., 2013). Both scenarios show that the roles of employees will change substantially. Under the human-centered tool scenario, humans make the major decisions guided by the CPS and take corrective action in the automated process. Under the automation scenario, decision-making shifts to the technical sphere of the production system (Dworschak et al., 2013). Furthermore, the employees with different interdisciplinary backgrounds have to coordinate themselves. Under the latter scenario, intelligent CPS can run the entire production and human competencies are only needed when systems are installed, modified and updated or if problems occur. In addition, employees will also be required as high-level problem solvers when machine intelligence is not able to deal with emergencies, system failure or other problems (Becker, 2015; Bochum, 2015; Dworschak and Zaiser, 2014; Windelband et al., 2013).

Table II–3: Scenarios in CPS[6]

Automation Scenario	Tool Scenario
▪ CPS guides skilled workers ▪ Work is determined by technology ▪ Autonomy of skilled workers is limited ▪ Emergence of a skill gap: Skilled workers cannot develop/build up the know-how for dealing with problems anymore ▪ High-skilled employees are responsible for installation, modification and maintenance of CPS.	▪ Skilled workers guide CPS ▪ CPS is the central domain of skilled workers. ▪ CPS supports the decision-making of skilled workers. ▪ A successful performance requires the provision of crucial information and suitable approaches of vocational education and training due to an increasing demand for IT, electronic and mechanical knowledge.

The content of the task: Autor and Dorn (2013) hypothesize that employees will perform more creative, problem-solving and coordination tasks that cannot be substituted by computers and algorithms. Frey and Osborne (2013) refer to this as ‘engineering bottlenecks’, where computers cannot substitute humans. These bottlenecks are tasks that require perception and manipulation, social intelligence or creativity (Frey and Osborne, 2013).

[6] Dworschak and Zaiser, 2014.

- **Perception and manipulation tasks:** For these tasks, employees require skills that enable them to structure and understand **complex and unstructured environments**. For example, machines are often not able to identify complex process failures and to develop solutions for some problems, such as finding a mislabeled inventory item and reentering it into the process (Bonin et al., 2015; Frey and Osborne, 2013).
- **Creativity tasks:** Creativity is the ability to develop ideas or artifacts, which are new and valuable (Boden, 2003). These ideas could be for instance poems, cooking recipes or scientific theories or artifacts. Creativity is driven by using the brain's associative platforms and pattern recognition and is supported by the brain's complex network of neurons. Therefore, it cannot be expected that CPS will be able to fully substitute human creativity over the course of the next decades (Bonin et al., 2015; Frey and Osborne, 2013).
- **Collaborative tasks:** Social competencies can be regarded as the lubrication oil of organizations, ensuring that collaboration and processes yield the desired results. Typical examples of collaborative tasks that heavily rely on social intelligence are negotiations between two partners or the motivation of employees. Admittedly, some computers can already imitate the social interactions between humans with algorithms, but there is still the factor of human emotions during interaction processes and computers are not (yet) able to master the complexity of human interaction processes (Frey and Osborne, 2013). Frazzon et al. (2013) highlight flexibility and in particular the problem-solving competence of humans to develop their full potential. These soft skill aspects are often neglected in CPS research, and only a few approaches have attempted to analyze it (Wang, 2010). Solving complex and unstructured problems requires more cognitive operations and thus more cognitive skills (Jonassen, 2000) compared to solving non-complex and well-structured problems (Kluwe, 1995). As a result, we also have to emphasize altered interaction and collaboration, which consequently requires increased social intelligence. Table II–4 summarizes the changes of the task content.

Table II–4: Task Content Scenarios[7]

	Traditional Industry	CPS and Industrie 4.0
Task content	▪ More routine tasks ▪ Focused on one discipline ▪ More structured tasks with a clear goal	▪ Fewer routine tasks ▪ More interdisciplinary problems ▪ Unstructured tasks ▪ Perception and manipulation tasks ▪ Collaborative tasks ▪ Creative tasks ▪ Flexibility ▪ Increased scope for decision making

The interaction and collaboration of humans with systems and within work teams: CPS will change the interaction with and the control of the physical world by humans (Rajkumar et al., 2010). The interaction between humans and machines through sensors and also different interactions between humans will be an enormous challenge and might even question the acceptance of CPS by humans (acatech, 2011). The traditional workplace in the office will become less important, because digital networks and the availability of real-time data allow physical production activities to be managed from anywhere. As a result, the task spectrum of many employees will increase (Gorecky et al., 2014). In addition, CPS will increasingly involve diverse groups in communication and interaction processes. Consequently, there will be a need for new concepts of collaboration (Linke, 2015) and structuring of the work between humans and machines (Becker, 2015). Schuh et al. (2014) present a framework for collaborative practices in Industrie 4.0 environments and they exemplify that different dimensions of collaboration (communication, coordination, cooperation) can be levers for CPS. Hirsch-Kreinsen (2014) and others highlight that employees with high qualifications and high flexibility within a loose network will have to solve problems collaboratively and in a self-organized manner – a concept comparable to swarm intelligence. They will use informal social processes for communication and cooperation to organize their specialized knowledge (Cummings and Bruni, 2009; Hirsch-Kreinsen, 2014; Neef and Burmeister, 2005). Concepts such as open production or open innovation will become more relevant (Basmer et al., 2015) and foster these trends and the need for a closer look at the necessary competence categories. Especially communication and interaction (human-to-human and human-to-machine) are vital aspects of these concepts. Even though technical competencies will remain important, it is obvious that soft skills (social, personal and – in parts – also methodological skills) will be

[7] based on: Bonin et al., 2015; Dworschak and Zaiser, 2014; Dworschak et al., 2013; Frey and Osborne, 2013.

given increased attention in relation to professional competency (Bauer et al. 2015; Meyer, Brunig, and Nyhuis 2015; Moraal, Lorig, and Schreiber 2009).

5 Development of a Measurement Instrument for Competencies in the Age of CPS

To categorize and to measure the necessary competencies for CPS, we propose the following scale that has been derived and further developed from that of North et al. (2013) and adapted to the requirements determined for CPS. Table II–5 summarizes our discussion. In general, we conclude that CPS will stimulate a shift of many of the criteria to the right-hand side of Table II–5, indicating less structured tasks and more interdisciplinary collaboration and problem-solving abilities. As a result, we divide the already existing dimension complexity of the tasks into technological complexity and contextual complexity. For contextual complexity, we distinguish three different dimensions of task structure, task content and interactiveness. Self-management skills and reflection capabilities complete our taxonomy.

Table II–5: Evaluation of Competencies for CPS[8]

<table>
<tr><th colspan="2"></th><th colspan="2">Connoisseur</th><th colspan="2">Experienced and advanced</th><th colspan="2">Expert and creative problem solver</th></tr>
<tr><td colspan="2">Role</td><td colspan="2">▪ Operator with low or basic competence levels</td><td colspan="2">▪ Experienced operator with intermediate competence levels</td><td colspan="2">▪ Creative problem solver
▪ Decision maker
▪ Teacher</td></tr>
<tr><td colspan="2"></td><td>A1</td><td>A2</td><td>B1</td><td>B2</td><td>C1</td><td>C2</td></tr>
<tr><td colspan="2">Knowledge and experience</td><td colspan="2">Basic Knowledge</td><td colspan="2">⟷</td><td colspan="2">Detailed knowledge and broad experience from different contexts and ability to train others</td></tr>
<tr><td colspan="2">Technological complexity of the task</td><td colspan="2">No technical background necessary</td><td colspan="2">⟷</td><td colspan="2">Challenging technical complexity with new and different systems and intensive interaction in interdisciplinary teams</td></tr>
<tr><td rowspan="3">Contextual complexity of the task</td><td>Structure of the task</td><td colspan="2">Clearly structured tasks</td><td colspan="2">⟷</td><td colspan="2">Challenging and new, unstructured tasks changing, depending on different and unknown contexts</td></tr>
<tr><td>Content of the task</td><td colspan="2">Routine tasks</td><td colspan="2">⟷</td><td colspan="2">Previously unknown situations and tasks, in interdisciplinary teams, creative solutions are required</td></tr>
<tr><td>Inter-action and collabo-ration</td><td colspan="2">Single discipline without any technical interaction and collaboration with others</td><td colspan="2">⟷</td><td colspan="2">High interdisciplinary and rapidly changing teams with different backgrounds; interaction only through technical interfaces with human and machine intelligence</td></tr>
<tr><td colspan="2">Independent work and self-management</td><td colspan="2">Work under guidance and with support from others</td><td colspan="2">⟷</td><td colspan="2">Independent and flexible work requiring creative and innovative solutions Interaction with machines and humans Leadership skills are crucial</td></tr>
<tr><td colspan="2">Reflection capability</td><td colspan="2">I can judge my actions and optimize them within the given framework</td><td colspan="2">⟷</td><td colspan="2">I can reflect on my actions, detect errors and misconduct and can use my knowledge for the expansion, differentiation and optimization of my actions</td></tr>
</table>

[8] based and extended on: North et al., 2013.

6 Conclusions

The manufacturing environment is changing, as the environment for employees in the manufacturing industry. Increasingly, routine jobs or tasks will be automated. Employees have to handle new technological and contextual complexities which determine their new role, content of tasks as well as interaction and collaboration procedures. Technological complexities can be addressed by refining the content of traditional qualifications. A rising contextual complexity is becoming relevant, however, especially in tasks which require more social and personal competencies. Due to factors such as increased flexibility, the roles of employees will change substantially. Employees will have to broaden their competencies in order to handle unstructured situations involving uncertainty. Furthermore, it will be necessary for them to work in teams with different interdisciplinary backgrounds in order to solve problems. Often, it will be necessary to communicate via interfaces, in different languages and across different time zones.

We have categorized different types of competencies which will be necessary for employees to work successfully in CPS environments. There is an increasing challenge for employees to learn continuously and to develop on-the-job competencies. Therefore, we suggest a measurement instrument for these competencies and demonstrate how the included technical and collaborative competencies provide guidance for mastering the technological and contextual complexity of CPS. Planning and managing these critical competencies are a crucial factor of CPS-based production systems. With the rise of new technologies there is also a need to define organizational competencies more precisely in order to successfully handle these complex environments.

These new roles, task content and interaction behaviors might overburden employees however, while simple and repetitive tasks will become increasingly automated (Hirsch-Kreinsen, 2014). The success of workers will depend on their flexibility, problem solving competencies as well as their willingness to engage in lifelong learning; otherwise, they will not be able to keep up with the required changes in their workplaces and work procedures. This challenge might also explain why many companies are reluctant to invest in CPS. We therefore conclude that competence management on the organizational level as well as the reform of public education (including the German apprenticeship/trainee system) are important factors for introducing CPS.

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III Research Paper 2: The Monetary Value of Competencies: A Novel Method and Case Study in Smart Manufacturing

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Abstract: Driven by technological transformation, changing competency requirements are receiving increasing attention. Technological developments, such as digitization, automation, and cyber-physical systems, will change occupational requirements. Additionally, many companies are already confronted with a shortage of a skilled workforce due to demographic change. These developments will cause future problems for the economic performance of several companies. Companies can satisfy their demand for skilled labor through training or hiring. Both options are expensive and require careful planning. Companies typically plan their processes and resources carefully. However, human capital is often neglected in the planning process. Consequently, companies should value competencies more and might even employ monetary-based evaluation methods to analyze their current organizational and employee competencies and to coordinate their human and financial resources. For this purpose, we chose to investigate which competencies will be required by mechatronics technicians if they are to master the new technological challenges of smart manufacturing systems and the associated complexities. Employing a budget-allocation approach, our study is based on a survey of 228 human resource and production managers. These managers are willing to allocate a relatively high budget to competencies such as complex problem-solving, analytical thinking, and troubleshooting. In addition, domain-based knowledge remains essential and valuable.

1 Introduction

Scientists and practitioners alike are referring to current developments in manufacturing technologies as the ‘fourth industrial revolution’, which is expected to fundamentally change the work environment. The technological developments are characterized by new and advanced technologies, such as cyber-physical systems, internet of things, big data, automation of production, digitization, smart factories, cloud computing, or additive manufacturing, which are used independently or in combination as innovative approaches for improving manufacturing and logistics processes (e.g., Bauernhansl 2014; Lasi et al. 2014; Oesterreich and Teuteberg 2016). Due to related rapid technological changes, the future workforce will face new competency requirements. Accordingly, companies have to adjust their employee selection processes and their investments in training measures in order to keep their employees – and ultimately themselves – competitive (Bonin et al., 2015; Frey and Osborne, 2013; Letmathe and Schinner, 2017; Mehra et al., 2014). Indeed, industries are already urgently searching for experts with knowledge in IT and mechatronics (WGP, 2018). However, these new technological developments do not only impact manufacturing companies. For instance, Koch-Rogge and Westermann (2017) highlight the importance of highly skilled employees in the banking sector, addressing the emerging digitized business models and services. Hence, various industries have to adapt their employees’ competency portfolios to be able to utilize the full potential of emerging technologies (Dworschak et al., 2013; Kagermann et al., 2013).

In order to further develop their employees’ competencies related to the new technological challenges, companies first need to identify relevant competencies. Although there is a lively discussion among researchers about what kind of competencies might be of particular importance for the future workforce (Autor, 2015; Autor and Dorn, 2013; Autor and Handel, 2013; Bauer et al., 2015b; Meyer et al., 2015; Moraal et al., 2009), there is surprisingly little research aimed at increasing the knowledge about the underlying measures’ validity and whether these measures provide sufficient insights about the consequences for companies and employees. There is an apparent gap between the assessment of work-related competencies and the practical consequences of this gap. In detail, whereas future competency importance is typically assessed by experts via Likert-type scales with different degrees of ‘importance’ attributed to the specific competency (e.g., Meyer, Brunig, and Nyhuis 2015) or through qualitative methods such as the critical incident technique (Robinson et al. 2007), the consequences for companies are financial, and decisions should therefore be based on monetary values, such as higher wages for more competent employees (e.g., Burrus et al. 2014) or increasing investments for training programs to further develop existing competencies of employees (Seyda and Placke, 2017).

To close this gap, our first contribution to the literature is methodological. We introduce a novel monetary-based measurement method in order to determine the value of future work-related competencies. Our measure assesses the monetary value of specific competencies that may be directly decision-relevant for companies, i.e., informing companies about how much to invest in the development of a certain competency relative to other competencies, either by paying higher wages or investing in additional training. Moreover, our measure allows the identification of critical financial values associated with the minimal and the optimal level of different competencies related to the future workforce.

As a second contribution, we apply this novel method to a case study on blue-collar workers, specifically from the mechatronics sector, in order to identify their required competencies for the digital age. We invited HR and production managers from the mechanical engineering and electrical engineering sectors, who are the main employers of mechatronics professionals. Each of our 228 participants was asked to indicate how much they would be willing to pay for certain competencies in order to meet the new challenges of technological developments. Our case study not only shows how to apply this method of assessing work-related competencies; it also provides important insights on experts' valuation of future requirements in employees' competencies.

This paper proceeds as follows: In the remainder of this section, we provide a detailed overview of theoretical aspects and measurements of work-related competencies, and introduce monetary-based evaluations of future competencies as a novel approach for competency management. In Section 2, we introduce the setting and method of our case study. Section 3 presents the empirical results. In Section 4 we draw broader conclusions from our results and the proposed measurement approach, including potential avenues for future research and implications for practice regarding competency measurement.

1.1 Competency Requirements in the Work Context: Definitions and Measurement Methods

According to Spencer and Spencer (1993, 9), '*competency is an underlying characteristic of an individual that is causally related to criterion-referenced effective and/or superior performance in a job or situation*.' The underlying characteristics proposed by these authors are knowledge, skills, self-concept, motives, and traits. In their so-called iceberg model of competencies, knowledge and skills are more 'visible' and easier to develop through training than the core personality (traits, motives) of an employee, which is considered as more stable (Spencer and Spencer, 1993).

Competency models help companies to systematically describe and evaluate the relevant competencies (Erpenbeck and von Rosenstiel, 2007; Mello, 2015; Reinhardt and North, 2003). In this context, several authors use competency models that contain differences in individuals' Knowledge, Skills, Abilities, and Other characteristics (KSAO; e.g., Campion et al. 2011) to describe and structure relevant competencies. First, different facets of domain-specific knowledge or technical expertise often represent hard or technical competencies that employees must possess to fulfill their job duties (Robles, 2012), e.g., mechanical knowledge. Second, skills are often related to procedural knowledge (Brannick et al., 2012) and they depend on experience and education and are not a permanent characteristic of an employee by default, e.g., complex problem-solving (Peterson et al., 1999). Third, an ability helps an employee to perform a certain task. This attribute is relatively enduring over the individual's lifespan (Tippins and Hilton, 2010). Abilities are traits that may develop over time but can also exhibit a sustained stability over periods, e.g., problem sensitivity. And fourth, other characteristics are, for example, personality traits or values. For example, work styles (e.g., dependability) are referred to in this category (Golubovich et al., 2017).

Besides, companies should take into account (perceived) improvements between the different categories of KSAOs (Maurer et al., 2003; Maurer and Lippstreu, 2008; Spencer and Spencer, 1993) when they try to synchronize individual competencies with their organizational needs. When it comes to knowledge that can be codified, companies might rely on paper-based or digital work instructions (Letmathe and Rößler, 2021) or other knowledge bases respectively. If skills need to be developed, training could serve as an appropriate solution. Further, personal action plans could help develop the abilities of the employees (Laube, 2013). Other characteristics related to core personality characteristics (e.g., work styles) are more difficult to develop but are crucial moderators of effective improvement of knowledge, skills, and abilities.

To identify which competencies should be selected or improved for a certain task or job, the competencies need to be assessed in the first place. Questionnaires with rating instruments are frequently used to ask about future competency requirements. For example, the importance of a specific competency for a job can be categorized on Likert-type scales (e.g., 5-point scales, O*Net n.d.; 4-point scales, Meyer, Brunig, and Nyhuis 2015). With these questions it is possible to answer which competencies are or will be important in the future. Still, it remains open at which level the competencies are necessary or even economically beneficial. Therefore, some of these scales use predefined anchors to refer different responses on the scale to different levels of (required) performance (Biesma et al., 2007; Grote et al., 2006; Letmathe and Schinner, 2017; North et al., 2013).

Yet, competency forecasting and measurement based on such importance scales also face criticism. For instance, the descriptors are often not specific enough and too general to inform specific outcome measures, e.g., training needs. Moreover, the meanings of scale points are often unclear to the respondents. The difference between 'somewhat important' and 'very important', for example, remains largely subjective from the perspective of the respective participant (Tippins and Hilton, 2010). Furthermore, it is easy for the rater to say every competency is important, but this does not capture the monetary trade-off between different attributes (Netzer and Srinivasan, 2011; Schlereth et al., 2014), e.g., what competencies should be prioritized and developed through training. Therefore, arguably, these ratings are mainly useful for comparisons but hardly for corporate decision-making and financial investments in the development of competencies (Tippins and Hilton, 2010). Even more elaborated indirect methods, such as discrete choice (e.g., Biesma et al. 2007) or qualitative approaches (e.g., Delphi studies, Critical Incident Technique; e.g., Robinson et al. 2007), mostly neglect the (future) monetary value of competencies and, hence provide just partial indications of to what extent companies should invest in competencies (Vooren et al., 2019).

Therefore, in the following section, we provide a short overview of why the monetary measurement of competencies is promising and helpful for companies in order to plan their employee selection, training, and retention processes. We then propose a complementary approach to measure work-related competencies and to evaluate them monetarily.

1.2 The Monetary Value and Assessment of Competencies

Clearly, money is a 'language' every company should understand and one which they apply to plan other resources in order to steer their performance. For materials, technology, machines, and other resources, monetary metrics already exist to evaluate and calculate investments. More and more companies also view employee competencies as a scarce resource that should be planned and evaluated in order for companies to stay competitive and satisfy their demand for skilled labor. A monetary evaluation is useful to determine (i) what wage to pay a highly qualified employee (compared to a less qualified employee) and (ii) what resources to invest in training of employees to increase their competencies, aimed at reaching a net benefit for the company. A sound monetary evaluation of competencies would allow (managers of) companies to put their portfolio of (required or offered) competencies into an economic framework (Vooren et al., 2019). Managers could even perform cost-benefit calculations of investments to strengthen certain work-related competencies and to optimize their portfolio of employee competencies (Mehra et al., 2014). The existing studies which determine monetary value of competencies are often based on historical data and the indicators cannot predict the required future preferences, for instance, due to massive technological changes in the manufacturing sector (e.g., Deming 2017; Hanushek et al. 2017; Kelly, O'Connell, and Smyth 2010).

Seminal studies on the monetary evaluations of future work-related competencies have been conducted by Humburg and van der Velden (2015) and Vooren et al. (2019). Humburg and van der Velden (2015) used discrete choice experiments for eliciting employers' future monetary competency values and potential return for higher competency levels. The authors provided potential employers with values of six competencies (professional expertise, general academic skills, innovative/creative skills, strategic/organizational skills, interpersonal skills, commercial/entrepreneurial skills) and a starting salary that they have to pay if they hire the candidate. They found that employers prefer candidates with higher professional expertise and interpersonal competencies. More importantly, employers were also willing to pay more for higher levels of these competencies. Vooren et al. (2019) analyzed the monetary value of soft and hard skills of information-technology retrainees. Through marginal rates of substitution, they provide some indication of the monetary value of the levels of education, fields of degree, experience in programming, and three soft competencies (listening skills, verbal communication, and teamworking skills). They found that – after programming experience – listening was the second most important competency, whereas verbal communication got the lowest value.

Although these studies can be seen as a first proof-of-concept of the feasibility of monetary evaluations of future work-related competencies, they only assessed very few generic competencies. We therefore extend the approach of these studies both on the level of measurement as well as concerning the evaluated competencies. For this purpose, we propose a two-step approach. The first step is to identify the most important competencies that a candidate must have or that should be trained. Simple importance ratings on Likert-type scales are sufficient at this stage to narrow down the range of potentially important competencies. In the second step, we exploit the conceptual advantages of monetary evaluations of competencies. We build on and extend previous research using a constant-sum mechanism to determine the importance of attributes, i.e., with regard to different categories of competencies. That is, respondents have to allocate a constant-sum budget to determine the importance of attributes (Hair et al. 2015). Constant-sum mechanisms are favorable to other direct valuation methods, such as rating scales or rank orders. They provide a ranking and also the magnitude of the relative importance of the different attributes (Hair et al. 2015)). Hence, with the constant-sum scale, a simultaneous comparison and evaluation of all characteristics implicitly takes place (Eckert and Schaaf, 2009; Schlereth et al., 2014). Concerning the limited overall budget, the respondent is forced to make trade-offs between different attributes into account (Hair et al. 2015; Schmidt 1996). This is an advantage compared to direct and indirect traditional willingness-to-pay methods, since a so-called yea-saying behavior is suppressed through budget constraints (Costa-Font et al., 2015; Vringer et al., 2017). Moreover, budget allocations based on constant-sum mechanisms are easy to apply (Eckert and Schaaf, 2009) and constitute a direct method in research and practice to assess the importance of attributes and preferences in various domains of research and practice (Blomquist et al., 2004; Buchanan and Huczynski, 1991; Costa-Font et al., 2015; Doyle et al., 1997; Jackson and Chapman, 2012). Previous research indicates that monetary valuations based on hypothetical budget allocations yield results that are applicable to real-life situations (Mitchell and Carson, 2005).

1.3 Case Study: Competencies of Blue-Collar Workers for Smart Manufacturing Workplaces

We apply our proposed monetary evaluation of employees' competencies to a case study on work-related competencies in the field of blue-collar workers. In particular, we focus on mechatronics technicians and their relevant competencies to master the challenges of smart manufacturing.[1] Blue-collar workers are defined as skilled or non-skilled workers who perform physical labor, typically in agriculture, manufacturing, construction, and mining (Berman, Bound, and Griliches 1994; Mittal, Dhiman, and Lamba 2019). Frey and Osborne (2013) showed that 47 % of the jobs in the US have the potential to be substituted by automation. Particularly classic blue-collar jobs have a high risk of being automated, as they often contain routine tasks.

Therefore, future workers will have to perform fewer routine tasks which cannot be automated by computers or machines (e.g., Bonin, Gregory, and Zierah 2015; Dworschak et al. 2013; Frey and Osborne 2015; Ras et al. 2017). Consequently, the roles of blue-collar workers will change substantially. For instance, they will have to perform more interdisciplinary, managerial, and collaborative tasks in teams to solve complex problems. For that purpose, blue-collar workers will likely need more personal and social competencies, such as cooperation and communication competencies (Haeffner and Panuwatwanich 2018; Pfeiffer et al. 2016). Soft skills relevant to the introduction of smart manufacturing (e.g., skills such as active learning)

[1] The term 'Industry 4.0' was used throughout the survey, as the study was conducted in Germany and this term is more common there. In the following, we use 'smart manufacturing' as a synonym for Industry 4.0 (Sniderman, Mahto, and Cotteleer 2016).

have also already been listed in the training regulations for metal and electrical occupations in Germany since 2003/04. Although soft factors are critical for adapting to the technological and organizational changes in order to utilize the full potential of new technologies (Dworschak and Zaiser 2014), previous studies on employee competencies in smart manufacturing have often neglected such factors. In addition, workers will also need to acquire higher competency levels, such as programming and software skills, that were previously performed by engineers (Haeffner and Panuwatwanich 2018). As a result, the boundaries between blue-collar workers and white-collar employees will become increasingly blurred (Kagermann, Wahlster, and Helbig 2013; Prause and Weigand 2016; Spath et al. 2013).

With these considerations and in light of the increasing merging of mechanical and electrical engineering as well as computer science in companies (Kärcher 2015), we focus on the profession of mechatronics, which requires an apprenticeship of at least 3.5 years in Germany. The interdisciplinary occupational profile of mechatronics technicians combines the fields of electrical engineering, mechanics, and computer science/IT technology (Müller 2005). It is a state-recognized training occupation in the German dual vocational education system with comparable requirements for all trainees (BMJV n.d.; Ehrenberg-Silies et al. 2017). The job profile is often mentioned in the context of smart manufacturing due to its interdisciplinary orientation and its suitability for the new task requirements in the context of smart manufacturing (Hacioglu 2019; Pfeiffer et al. 2016; Spöttl et al. 2016). In 2018, the training regulations for mechatronic technicians were already adapted to the requirements of smart manufacturing. For example, additional qualifications such as programming were added (Weinzierl 2018). Additionally, the demands on the mechatronics technician's communication skills are also increasing because complex problem solutions in modern organizations require cooperation across disciplines (Ehrenberg-Silies et al. 2017). Potentially related to these increased demands, the German mechanical and electrical engineering industry suffers from a shortage of skilled workers in this area and has already responded with an increased offer of apprenticeships (Malin et al. 2018). Relatedly, wages and tasks vary substantially between different occupations and with different experience levels (Rotundo and Sackett 2004). This is why the job profile of mechatronics technicians is particularly well suited for a monetary evaluation of future competencies.

2 Methodology

2.1 Participants

We invited HR and production managers – as the main groups that are involved in the employee selection and training processes –from the mechanical engineering and electrical engineering sector, given that mechatronics professionals are mainly employed in these sectors[2]. Managers from the HR and production fields are particularly interesting as they typically have a different focus in their education and in their daily work (Boudreau et al., 2003). We only invited managers from companies with more than 50 employees in order to ensure a minimum standard for the relevant HR processes.

Table III–1: Descriptive Statistics of the Sample

		n	*Percent*
Function			
	HR	106	46.5 %
	Production	37	16.2 %
	Both	37	16.2 %
	Other	47	20.6 %
Sex			
	Male	174	76.3 %
	Female	54	23.7 %
Firm size			
	SME	84	36.8 %
	Large enterprise	144	63.2 %

Note. Numbers may not add up to 228 due to missing values.

In total, n = 228 respondents completed the study. Table III–1 shows the most important descriptive statistics from the sample. The majority of the respondents in the sample were male (76.3 %) with an average age of 44.03 years and an average work experience of 19.16 years. Almost half of the respondents were HR managers ($n = 106$) and 63.2 % ($n = 144$) of the

[2] Contact information was retrieved from the following sources: The database 'Nexis' (formerly LexisNexis / Wirtschaft) offers company and financial information as well as information about managers from the respective companies. Furthermore, the company data from 'Nexis' is collected from databases such as Bundesanzeiger, Creditreform, Handelsregister, Hoover's, Experian Corpfin as well as the Bisnode/Hoppenstedt Firmendatenbank.

respondents work in large companies with more than 500 employees and a turnover of more than € 50 million.[3]

2.2 Measures

First, we derived 43 competencies from the O*NET[4] items of knowledge, skills, abilities, and work styles, which were considered as relevant for the profession of mechatronics. O*NET has been shown to be particularly suitable for work-related applications, such as employee selection and training (Converse et al., 2004; Maurer and Lippstreu, 2008). The O*NET items are suitable because they correlate with actual wages (Handel 2016) and, furthermore, their importance ratings yield comparable results in different countries (Taylor et al., 2008). Two bilingual translators from our department, whose native language is German, translated the descriptions from the O*NET Database into German, and the differences between both translators were corrected after discussion. A third translator, whose native language is English, back-translated the items. The discrepancies were corrected accordingly. Next, seven selected industry experts rated the importance of each of the 44[5] competencies in order to meet the requirements for coping with the new challenges posed by smart manufacturing. For this, we used a five-point Likert scale, from 1 = 'not important' to 5 = 'very important'. Then, we selected the four highest-rated competencies for each category (KSAO) – hence, 16 competencies overall – to be included in the study (see Table III–2) and evaluated by the respondents. In detail, every respondent evaluated a given competency (by providing a monetary value, see procedure below) for both the minimal and the optimal level particularly for the profession of mechatronics professionals.

Damschroder et al. (2007) argue that asking for a percentage of financial resources on a monthly basis results in promising improvements and less questionable values. As people and companies often plan their budgets on a monthly basis (e.g., monthly salary cost for an employee), we asked for the willingness to allocate the budget given to an employee on a monthly basis. Due to the importance of the budget constraint in allocating funds for flexible salaries (Fam and Yang, 2006; Smith, 2005), we derived a realistic budget from the database of GEHALT.de[6]. Accordingly, we assume a budget of €1000 to capture the fluctuations of

[3] We distinguish small and medium-sized enterprises (SMEs) from large enterprises using turnover (< € 50 million) and number of employees (< 500 employees) according to the SME definition of the IfM in Bonn.

[4] O*NET is one of the most complete repositories of job information and contains comparable descriptions and scales of work-relevant competencies (Taylor et al., 2008; Tippins and Hilton, 2010).

[5] Electrical Engineering Knowledge is not a part of the O*NET dictionary. We added this knowledge category as a counterpart for Mechanical Knowledge after discussions with industry experts.

[6] GEHALT.de is the leading salary information portal in German-speaking countries. All salary data on GEHALT.de is examined by advisors for plausibility. The data are determined by surveys among employees or companies.

payments for the mechatronics domain in Germany between different regions, i.e., differences in salaries. We divide this budget into 500 € for every competency level (minimal vs. optimal) and asked respondents to allocate this amount. Specifically, respondents decide on the amount of the (additional) salary for an employee who is assumed to have a certain competency at a minimal level, and at the same time what they would be willing to pay from the additional budget of 500 € if the employee would have an optimal level of the respective competency beyond the minimal competency level. We explicitly allowed only parts of the budget to be distributed. Thus, we take into account the fact that companies could invest this money elsewhere. For instance, in reality, the budget for salary negotiations or offers of employment may not always be fully utilized. Furthermore, some competencies could be very important to fulfill the requirements of the jobs, but employers would not hire or pay more for this competency because it is considered a basic requirement for this job (Peterson et al., 1999). Consequently, respondents might value some competencies with zero. On the other hand, it is also possible that the specific competency is not valued at all for the job in the respective company, which would result in a zero allocation as well.

Table III–2: Selected KSAOs based on Experts' Opinion

Knowledge	*Skills*	*Abilities*	*Others*
Electrical Engineering	Complex Problem-Solving	Inductive Reasoning	Adaptability/ Flexibility
Computers and Electronics	Systems Analysis	Problem Sensitivity	Cooperation
Engineering and Technology	Troubleshooting	Information Ordering	Analytical Thinking
Mechanical Engineering	Active Learning	Deductive Reasoning	Dependability

To explain zero valuations and distinguish between these fundamentally different interpretations, we extended the study and asked the participants why they valued a certain competency with zero. Respondents had three options to choose from: (i) the competency is a basic requirement for a mechatronics technician and employers would therefore not pay more than the basic salary; (ii) the competency, in its respective form or on this level, has no additional monetary value; (iii) other reasons to be added in a free text field.

2.3 Procedure

The participants were recruited via e-mail to take part in an online survey through the software EFS survey. At the beginning of the survey, participants received instructions about the research aim and the procedure. Afterward, they had to answer socio-demographic questions. We then provided the participants with a complete task description of how the available budget has to be distributed and what the competency levels represent. Furthermore, there was also an explanation of the job description and the tasks of a mechatronic engineer. Additionally, participants were asked about the complexity of the field of activity of mechatronic engineers in their respective companies. Afterward, they were shown four exemplary scenarios for the evaluation of the competency characteristics.

Each participant received a list with the 16 competencies (see Table III–2). Then they were asked to indicate in Euros how much they would be willing to allocate from the budget to each competency at the minimal and optimal competency level in order to meet new challenges due to smart manufacturing. All of the 16 competencies were assessed at the same time separately for each level (first: minimal, second: optimal). We used different sequences of the competencies and balanced them to minimize response bias. The respective definitions provided for each competency are available in the Appendix. Participants were able to look at the definitions at any time via mouseover. Participants could see how much of the budget had already been allocated at any time. Finally, each participant in a sub-sample (the last n = 112 participants) had to indicate for each competency that was rated zero by this particular respondent, what the underlying reasoning for this response was (see above).

3 Results

3.1 Descriptives

The respondents allocated on average 86 % of the available budget (€ 1000) to the selected competencies (M = 859.65, SD = 234.56). For the minimal and the optimal competency category, 500 Euros were available to each participant. The average allocated budget in the minimal competency category (M_{min} = 405.11, SD = 152.11) was lower than for the optimal competency category (M_{opt} = *454.54,* SD = 108.89).

Across all evaluations, 31 % (min = 30,1 %; opt = 32 %) were valued with zero. Among the sub-sample of 112 participants who also indicated the reason for each competency that was rated with zero (for the sub-sample only: 28.8 % overall; 27.1 % of ‘abilities’; 26.4 % of ‘others’; 26.0 % of knowledge; 20.4 % of ‘skills’), the vast majority was attributed to the fact that this competency was a basic requirement (84.0 %; for a detailed overview of the single competencies, see Appendix III–2).

Figure III–1 presents the mean values of the budget-allocation for every single competency. The dark gray bar shows the average budget allocation for the minimal competency level, and the light gray bar depicts the average value for the optimal competency level. The high valuation of complex problem-solving in the skills category is particularly noticeable.

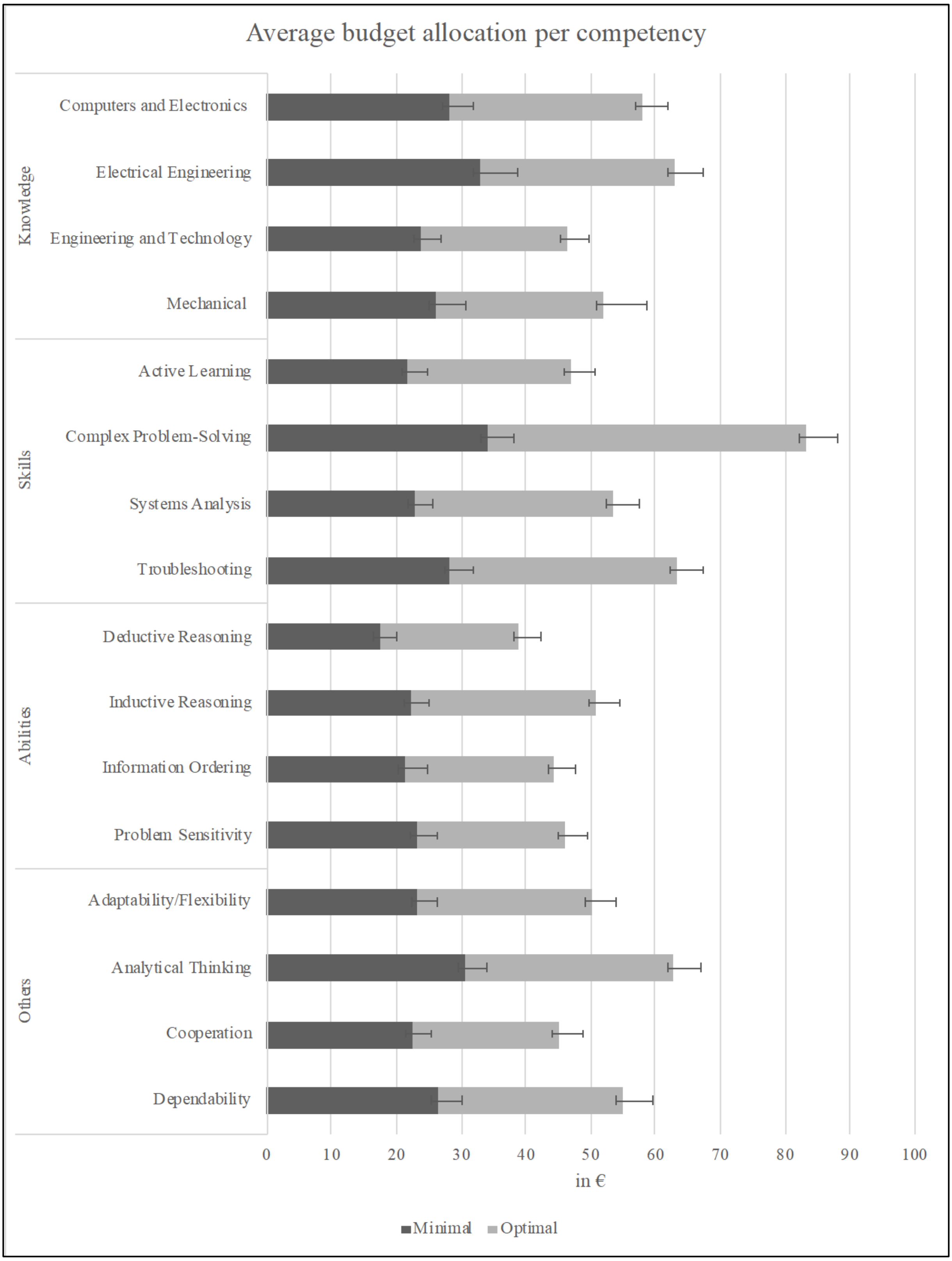

Figure III–1: Average Budget Allocation per Competency in Euro

Figure III–2 shows the mean values per competency category. Overall competencies in the category others (M_{min_others} = 102.86, SD = 67.07; M_{opt_others} = 110.25, SD = 81.67) received a lower budget than knowledge ($M_{min\_knowledge}$ = 110.86, SD = 87.66; $M_{opt\_knowledge}$ = 108.43, SD = 90.02). Vice versa, the category of skills receives the highest average values (M_{min_skills} = 107.21, SD = 63.98; M_{opt_skills} = 139.75, SD = 74.95). The competency category of abilities ($M_{min\_abilities}$ = 84.18, SD = 53.02; $M_{opt\_abilities}$ = 96.12, SD = 61.85) has much lower mean values than knowledge, skills, and others. Furthermore, we found that the respondents are willing to spend a higher amount for the optimal (vs. minimal) competency level. Hence, most competencies receive a higher share of the budget for the optimal competency level. Interestingly, electrical engineering, engineering and technology, and mechanical knowledge have a lower share of the budget for the optimal competency level than for the minimal competency level. These competencies are all from the knowledge category.

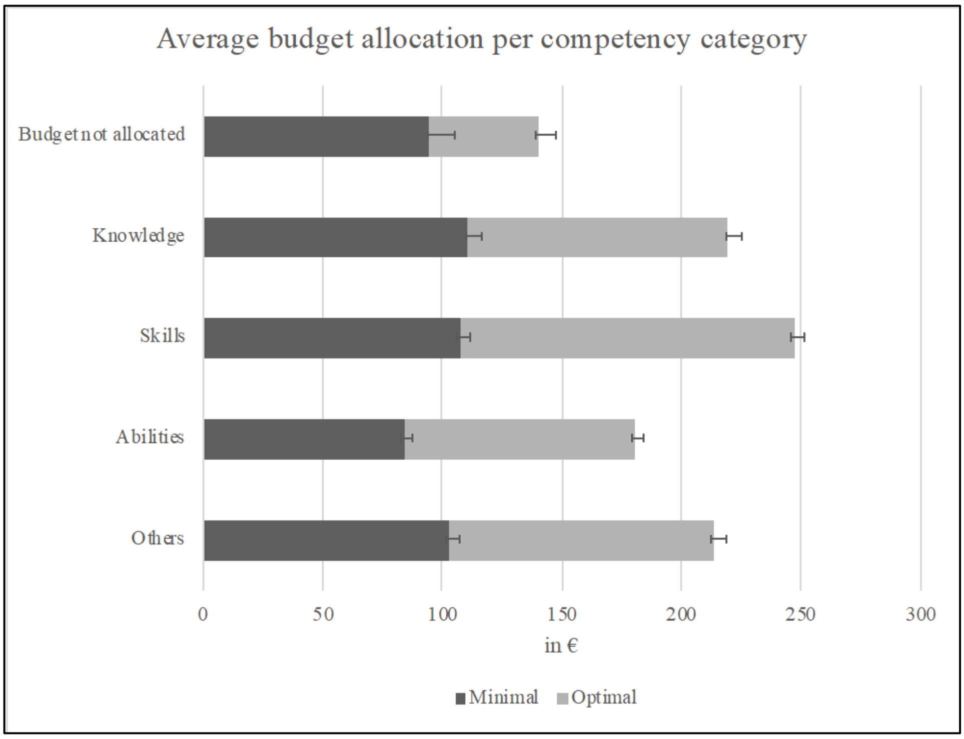

Figure III–2: Average Budget Allocation per Competency Category

3.2 Budget-Allocation for KSAOs

We tested the predictors of the budget allocation with a linear mixed effect model using the lme4 package (Bates et al., 2015) in the R framework (R Development Core Team, 2016). In Models 1–4 (see Table III–3 and Table III–4), we predicted the allocated budget as the dependent variable.

The knowledge category serves as the baseline category and is compared with skills, abilities, and other characteristics. The minimal level of competency serves as the baseline category and is compared to the optimal level. In all models, we control for the respondents' age and gender. We consider all effects with $p \leq .05$ as significant.

In Model 1, we found a higher willingness to allocate money for skills than for knowledge ($M_{skills} = 246.96$, $SD = 115.06$; $M_{knowledge} = 219.29$, $SD = 150.65$; $B = 3.46$, $SE = 0.99$, $p < .001$). This effect is mainly driven by the complex problem-solving competencies within the category skills, which has a higher mean value than any of the other competencies in our survey. Moreover, participants spent a smaller share of the budget on abilities ($M_{abilities} = 180.29$; $SD = 94.21$) than on knowledge ($B = -4.87$, $SE = 0.99$, $p < .001$). Regarding the different competency levels, participants allocated more funds in order to reach the optimal level compared to reaching the minimal level ($B = 3.09$, $SE = 0.70$, $p < .001$). In other words, reaching an optimal level of a competency resulted in a higher willingness-to-pay than reaching a minimal level of the same competency. Regarding participants' demographics, we found that younger managers exhibited a significantly lower willingness to spend money to raise the KSAOs of the employees than older ones did ($B = -0.11$, $SE = 0.05$, $p = .022$).

Model 2 adds the participants' management function as a predictor variable. HR management serves as the baseline category as compared to production management. Although production managers and HR managers did not show a significant difference in their willingness to spend their budget on all KSAOs, the additional variance captured by this predictor yields the effect of age and skills (compared to knowledge) as insignificant, whereas the other effects remain qualitatively the same.

Model 3 adds the interactions between competency categories and the competency level. In fact, there was only a positive and significant interaction of skills and the optimal competency level ($M_{min\_skills} = 107.21$, $SD = 63.98$; $M_{opt\_skills} = 139.75$, $SD = 74.95$). This indicates that the budget allocation to skills increased for the optimal competency level in comparison with the minimal competency level ($B = 8.75$, $SE = 1.97$, $p < .001$). In other words, skills are particularly valued at the optimal level.

Finally, Model 4 adds two-way interactions with participants' management function and, for completeness, the respective three-way interaction terms. Production managers allocated a higher share of their budget to others ($M_{HR} = 212.62$, $SD = 131.50$; $M_{Prod} = 249.49$, $SD = 150.83$) than HR managers ($B = 10.71$, $SE = 4.13$, $p = .010$). Moreover, a marginally significant interaction of skills and the management function exists ($B = 7.37$, $SE = 4.13$, $p = .074$), indicating that production managers valued skills somewhat more than HR managers did (M_{HR}

= 242.06, *SD* = 106.10, M_{Prod} = 237.78, *SD* = 126.90). Furthermore, a marginally significant effect of abilities and management function (*B* = 7.96, *SE* = 4.13; *p* = .053) suggests that production managers valued abilities (M_{HR} = 168.85, *SD* = 86.86; M_{Prod} = 186.49, *SD* = 104.30) slightly more than HR managers did. Yet, the marginally significant negative main effect of management function (*B* = -6.07, *SE* = 3.12, *p* = .054) suggests that HR managers, in contrast, valued knowledge somewhat more than production managers did (M_{HR} = 245.00, *SD* = 161.90; M_{Prod} = 191.43, *SD* = 132.22). There were no significant three-way interactions.

Table III–3: Linear Mixed Effect Model: Model 1 and Model 2

Predictor	Model 1			Model 2		
	B	*SE*	*p*	*B*	*SE*	*p*
(Intercept)	30.89	2.96	< .001	32.34	3.91	< .001
Competency field (Base Knowledge)						
Skills	3.46	0.99	< .001	1.23	1.28	.339
Abilities	-4.87	0.99	< .001	-7.22	1.28	< .001
Others	-0.77	0.99	.434	-1.12	1.28	.381
Competency level (Base: Minimal)						
Optimal	3.09	0.70	< .001	2.72	0.91	.003
Function (Base: Human Resource Management)						
Production Management				-0.23	1.51	.881
Controls						
Gender	-0.23	1.18	.849	-0.10	1.51	.510
Age	-0.11	0.05	.022	-0.08	0.06	.183
Observations/Individuals	7296/228			4576/143		
BIC (Bayes information criteria)	70449.39			44470.15		

Note: *B* = unstandardized regression coefficient; *SE* = standard error; *p* = p-value

Table III–4: Linear Mixed Effect Model: Model 3 and Model 4

Predictor	Model 3			Model 4		
	B	*SE*	*p*	*B*	*SE*	*p*
(Intercept)	32.73	3.03	< .001	35.76	4.05	< .001
Competency field (Base Knowledge)						
Skills	-0.91	1.39	.513	-5.25	2.10	.013
Abilities	-6.67	1.39	< .001	-10.44	2.10	< .001
Others	-2.00	1.39	.151	-5.08	2.10	.006
Competency level (Base: Minimal)						
Optimal	-0.61	1.39	.661	-0.71	2.10	.736
Function (Base: Human Resource Management)						
Production Management				-6.07	3.12	.054
Two-way interactions						
Skill*Optimal	8.75	1.97	< .001	9.76	2.97	.001
Abilities*Optimal	3.60	1.97	.068	1.85	2.97	.534
Others*Optimal	2.46	1.97	.213	3.51	2.97	.237
Skill*Production Management				7.37	4.13	.074
Abilities*Production Management				7.96	4.13	.053
Others*Production Management				10.71	4.13	.001
Opt*Production Management				-1.50	4.12	.716
Three-way interactions						
Skill*Optimal* Production Management				-2.43	5.84	.677
Abilities*Optimal* Production Management				1.87	5.84	.748
Others*Optimal*Production Management				1.18	5.84	.841
Controls						
Gender	-0.23	1.18	.849	-1.00	1.51	.509
Age	-0.11	0.05	.022	-0.08	0.06	.183
Observations/Individuals	7296/228			4576/143		
BIC (Bayes information criteria)	70446.22			44482.5		

Note: *B* = unstandardized regression coefficient; *SE* = standard error; *p* = p-value

4 Discussion

The primary purpose of this paper was to assign a monetary value to competencies using the mechatronics domain as an example. We apply the well-known KSAO competency descriptors within this budget-allocation approach. Our findings indicate that a future-oriented, monetary valuation may be helpful for organizational planning and development. We found several significant results within the valuation of the different KSAOs and between the different management roles that are involved in the employee selection, training, and retention processes. These results show the benefits and opportunities of this valuation method.

The skills category is the category most highly valued by all management roles. This effect is essentially driven by the high valuation of ‘complex problem-solving’ and ‘troubleshooting’. The problem-solving competency is particularly often cited in the literature as one of the most important competencies in the 21st century (Biesma et al., 2007; Letmathe and Schinner, 2017). Therefore, the high values determined for ‘complex problem-solving’ were not surprising. One reason is certainly the rise of complexity that is being added through new technologies (Dworschak and Zaiser, 2014; Kagermann et al., 2013). Additionally, other studies, which analyze historical data, also found a correlation between problem-solving competencies and wage (Autor and Handel 2013; Burrus et al. 2014). Some authors also highlight the importance of learning for the workforce in the 21st century to keep up with the technological changes (e.g., Finegold and Notabartolo 2010; Kyllonen 2012). Surprisingly, ‘active learning’ receives the smallest share of the budget in this category, which can partly be explained by it being frequently mentioned as a basic requirement for mechatronics professionals.

Knowledge competencies have the second-highest values. This is in line with the reasoning that different facets of domain-specific knowledge or technical expertise often represent competencies that employees must possess to fulfill their job duties (Robles, 2012). Our results show that this also leads to a higher willingness-to-pay for more knowledgeable employees. This has practical value especially because knowledge is likely to be one of the most obvious competencies when hiring new employees.

The category ‘abilities’ received a lower valuation than knowledge and skills. This result is not in line with the prominent literature, which sees reasoning as one of the trending competencies for the next decade (e.g., Leopold, Ratcheva, and Zahidi 2018). In contrast, we found low valuations for the competency ‘deductive reasoning’.

The valuation of other competencies is not significantly different from that of ‘knowledge’. Within the category ‘others’, the competency ‘cooperation’ has surprisingly low mean values for the minimal as well as for the optimal competency level. This result contradicts the argumentation of several authors who highlight cooperation competencies and working collaboratively as important levers for smart manufacturing (e.g., Schuh et al. 2014) and key competencies for future requirements (e.g., Biesma et al. 2007; Frey and Osborne 2013; Humburg and van der Velden 2015; Letmathe and Schinner 2017; Robles 2012). One explanation for this is that several participants regard cooperation to be a basic requirement that does not merit additional salary (see Appendix III–3). Likewise, many see 'dependability' as a basic requirement. Consequently, several respondents assign no value to this competency category. In contrast, 'analytical thinking' achieves high mean values in the competency category 'abilities.'

Furthermore, respondents value the optimal competency level significantly higher than the minimal competency level. Somewhat relatedly, Humburg and van der Velden (2015) state that a high level of professional expertise (which includes domain-specific knowledge) is particularly financially rewarded by employers. Future research is needed to better understand how different competency levels relate to different degrees of willingness-to-pay.

Surprisingly, in the knowledge category, 'electrical engineering', 'engineering and technology', and 'mechanical knowledge' receive lower mean values for the optimal competency level than for the minimal level. Probably some employers want to develop their employees and the latter´s domain-specific knowledge in the company's internal training facilities. Following this assumption, minimal competency levels would suffice in this area. Otherwise, employees with very high competency levels might quickly become bored if having to perform activities that are not very demanding of them (Humburg and van der Velden, 2015). Therefore, in some companies, the low level of competencies is probably fully sufficient. A more contrasting picture emerges in the skills category. In an increasingly complex working world, these skills help individuals to find solutions quickly and they increase employee performance. Therefore, managers value this competency category, especially beyond the minimal level.

Interestingly, HR managers value other competencies less than production managers do. It seems production managers focus more on competencies that are enduring, such as personal traits or motivation, and set different priorities than HR managers. The results from the production managers corroborate the ideas of Spencer and Spencer (1993) that companies should focus more on soft competencies that are enduring and not as easily trainable as knowledge is. Surprisingly, the HR managers value the knowledge category significantly more highly than the production managers do. This could be explained by the fact that production managers work more closely with mechatronics and may therefore assess the company's needs differently from HR managers. These findings are partially in line with the assumption of Spencer and Spencer (1993) that companies focus on more 'visible' competencies, which are often easier to observe, during the employee selection process.

4.1 Limitations

Our approach to valuing competencies monetarily has also some limitations. According to Brock et al. (2019), monetary value is a limited instrument and should not be the only instrument used. Particularly when analyzing competencies needed for the future, this approach would be too short-sighted. However, due to enormous investments in technology and the increasing costs of employee selection and training, the need for companies to avoid neglecting monetary values is obvious. Our aim was not to develop a framework for 21st century skills or smart manufacturing skills. Tests with different budget levels could help to acquire more information regarding the necessities of companies and other professions. In reality, budgets are different. To take this factor into account, we could also ask the participants about their possible budget in order to collect specific information about their individual willingness-to-pay. Probably, this would lead to further bias, and the values would not be as comparable as in our approach. It might also be possible to use choice sets. The generation of choice sets is often complex, and choice experiments also have several further problems, such as scope insensitivity, strategic biases, or warm glow (e.g., Søgaard, Lindholt, and Gyrd-Hansen 2012; Ryan et al. 2001; Chilton and Hutchinson 2000; Boyle et al. 1994) and respondents do not consider all alternatives when providing their ratings.

Future research could use our method to detect more differences in the valuation of competencies between groups such as production managers and HR managers. Both groups are involved in the employee selection and training processes but disclose different monetary preferences with regard to the competency categories. These differences can lead to sub-optimal selection and training processes.

4.2 Conclusion

It is not obvious how employers will pay employees with specific competencies in the future. Actual payments of employees depend on several developments, such as vocational training, school, university education, technological developments, demographics and the regulatory environment. Moreover, experts can only partially foresee technological developments in order to judge any potential competency gaps. Perhaps this is also one of the reasons for the high valuations of skills, abilities, and work styles. With unsecure developments, employers aim to stay flexible, with a highly reactive workforce that is capable of quickly adapting to new developments. Especially because institutional education (e.g., in schools) should increase employability (Rotundo and Sackett, 2004), it is advisable to further develop broad and soft competencies, such as problem-solving skills, which will effectively enhance the employability and value of an employee for a company and on the job market.

The total set of results observed in the current study strongly implies that the monetary valuation of KSAOs is a helpful additional tool that can be effectively used to understand aspects of occupational and organizational psychology. Also, this tool helps practitioners to discuss and build expectations uniformly among groups that are involved in the employee selection and training processes. Specifically, the valuation helps to gain a better understanding between important functions (HR and production) when they plan investments into human capital.

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Appendix

Appendix III–1: Descriptions for the Optimal and the Minimal Skill-Level

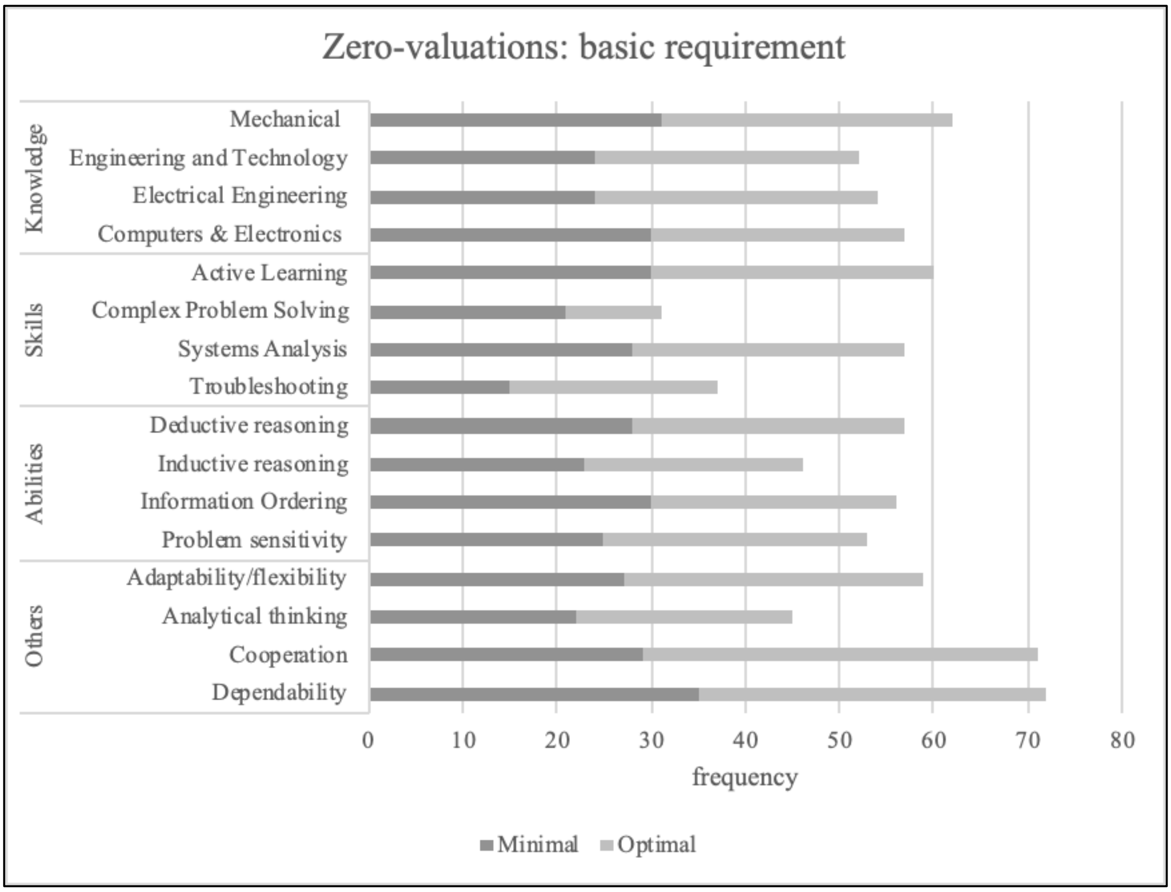
Skill-level	Description
Minimal	Without this level of competency, the regular work of a mechatronics professional cannot be accomplished or can only be accomplished with increased disturbances to the relevant processes. Usually, the employee at this competency level requires guidance in general or guidance from another employee or supervisor. The efficiency losses are at the level of the industry average.
Optimal	With this competency level, the respective mechatronics engineer can carry out the tasks of the future in the relevant processes independently and without guidance, even in an unusual context. The efficiency losses are significantly lower than the industry average.

Appendix III–2: Competency Descriptions[7]

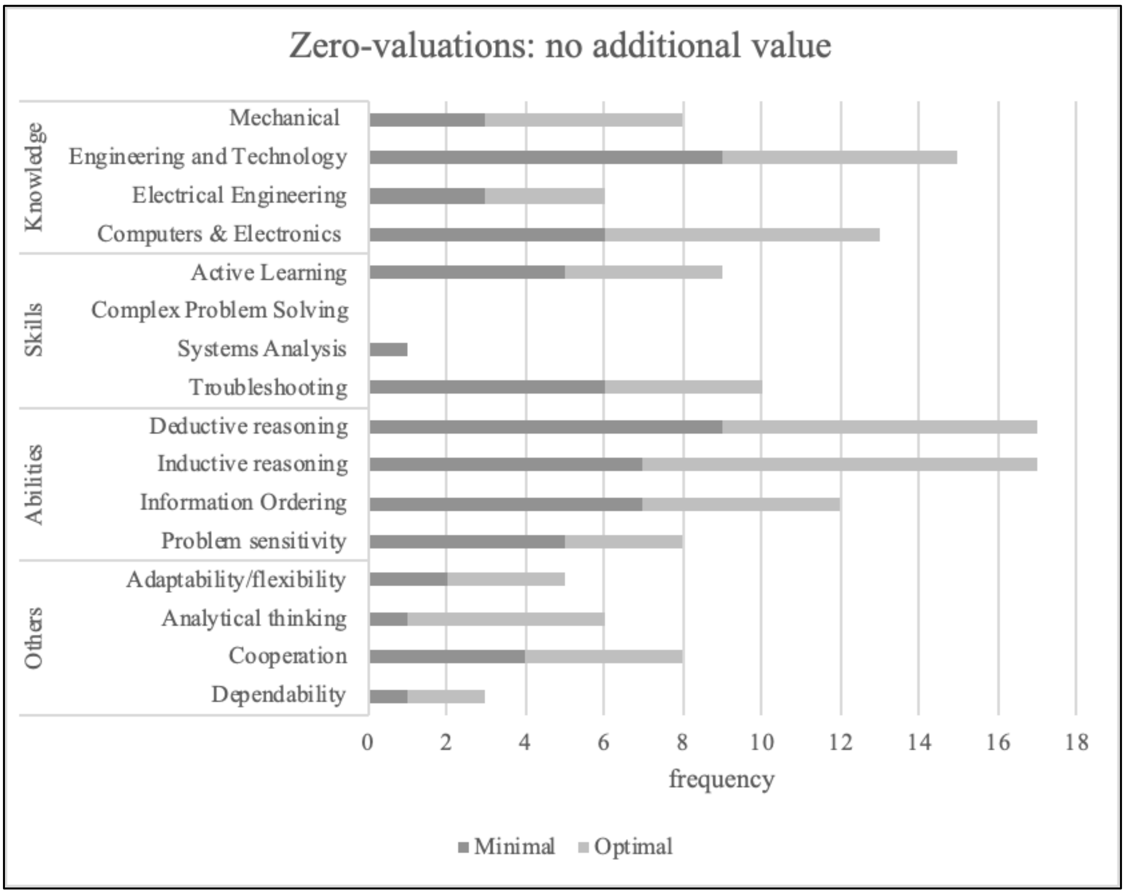
Competency	Description	Category
Mechanical	Knowledge of machines and tools, including their designs, uses, repair, and maintenance	Knowledge
Electrical Engineering	Electrotechnical knowledge of machines and tools, including their designs, uses, repair, and maintenance	Knowledge
Computers & Electronics	Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming	Knowledge
Engineering and Technology	Knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services.	Knowledge
Dependability	Job requires being reliable, responsible, and dependable, and fulfilling obligations	Work styles
Analytical Thinking	Job requires analyzing information and using logic to address work-related issues and problems	Work styles
Cooperation	Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude	Work styles
Adaptability/ Flexibility	Job requires being open to change (positive or negative) and to considerable variety in the workplace	Work styles
Complex Problem-Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions	Skills
Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making	Skills
Trouble-shooting	Determining causes of operating errors and deciding what to do about it	Skills
Systems Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes	Skills
Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g. patterns of numbers, letters, words, pictures, mathematical operations)	Abilities
Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense	Abilities
Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events)	Abilities
Problem sensitivity	The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem	Abilities

[7] The competency ‘electrical engineering knowledge’ is not part of the O*NET dictionary. We added this competency as a counterpart for ‘mechanical knowledge’ after discussion with the industry experts.

Appendix III–3: Zero-Valuations – Basic Requirement for a Mechatronics Professional



Appendix III–4: Zero-Valuations – No Additional Value for the Mechatronics Domain



Appendix III–5: Main Survey – (Original Version; in German)

14%

Sehr geehrte Damen und Herren,

an der RWTH Aachen University führen wir eine wissenschaftliche Studie zum Thema **„Der Wert von Kompetenzen im Zeitalter von Industrie 4.0"** durch. Ziel der Studie ist es, zu untersuchen, welche **Kompetenzen in Zukunft von Mechatronikern*** benötigt werden, um die neuen technologischen Herausforderungen durch Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende Komplexität der Arbeitswelt zu meistern. Dazu befragen wir Verantwortliche aus dem **Personal-** und aus dem **Produktionsmanagement.** Sie als Experte helfen somit, Implikationen für die **Ausbildung von Jugendlichen** zu entwickeln und diese dadurch besser auf die neue Arbeitswelt vorzubereiten.

Es würde uns sehr freuen, wenn Sie sich **5-10 Minuten Zeit** nehmen, um den folgenden Fragebogen auszufüllen. Als Dank lassen wir Ihnen gerne die detailierten **Ergebnisse der Studie** exklusiv vor der Veröffentlichung zukommen. Bei Interesse geben Sie dazu bitte am Ende des Fragebogens Ihre E-Mail-Adresse in einer separaten Umfrage an, so dass Ihre Anonymität weiterhin gesichert ist (alle Angaben werden streng vertraulich behandelt).

Sie können die Beantwortung des Fragebogens jederzeit unterbrechen und zu einem späteren Zeitpunkt fortfahren. Mit dem Link aus der E-Mail können Sie bis zur Beendigung des Fragebogens beliebig oft zurückkehren und damit die Beantwortung wieder aufnehmen.

Bei Fragen können Sie uns selbstverständlich gerne unter den unten angegebenen Kontaktdaten erreichen.

Wir bedanken uns für Ihre Unterstützung und wissen Ihre Zeit sehr zu schätzen!

Mit freundlichen Grüßen

Prof. Dr. Robert Böhm
Prof. Dr. Peter Letmathe
Dipl. Kfm. Matthias Schinner

Korrespondenzadresse:
Lehrstuhl für Controlling, RWTH Aachen University – Matthias Schinner – schinner@controlling.rwth-aachen.de

*Aus Gründen der besseren Lesbarkeit wird auf die gleichzeitige Verwendung männlicher und weiblicher Sprachformen verzichtet. Sämtliche Personenbezeichnungen gelten gleichwohl für beiderlei Geschlecht.

Weiter

29%

Alle Angaben, die Sie hier machen, sind freiwillig!

Bitte geben Sie Ihr Geschlecht an.

- Männlich
- Weiblich
- Sonstiges

Bitte geben Sie Ihre Funktion im Unternehmen an. ?

- Personalverantwortlicher/ Personalmanagement
- Produktionsverantwortlicher/ Produktionsmanagement
- In beiden Funktionen tätig
- Sonstiges:

Bitte geben Sie Ihr Alter (als ganze Zahl) an.

Jahre

Bitte geben Sie Ihren höchsten Bildungsstand an.

- Kein Abschluss
- Volks-/Hauptschule
- Realschule (mittlere Reife)
- (Fach-)Abitur
- Abgeschlossene Berufsausbildung
- Meister
- Bachelor
- Master
- Diplom
- Promotion

Bitte geben Sie Ihre Berufserfahrung, die Sie bereits ingesamt in ihrem Arbeitsleben gesammelt haben, in Jahren (als ganze Zahl) an.

Jahre

Bitte geben Sie Ihre derzeitige Position im Unternehmen an.
Falls keine der vorgeschlagenen Antwortmöglichkeiten zutrifft, geben Sie bitte so genau wie möglich Ihre Position an.

- Sachbearbeiter
- Fachreferent
- Gruppenleiter
- Teamleiter
- Abteilungsleiter
- Bereichsleiter
- Geschäftsführer
- Sonstiges:

Zurück Weiter

43%

Aufgabenbeschreibung:
Die folgenden Kompetenzen wurden von Experten für diese Studie ausgewählt und haben eine besondere Bedeutung für das **Berufsbild des Mechatronikers,** um die neuen technologischen Herausforderungen durch Vernetzung, Automatisierung sowie Digitalisierung der Produktion (zusammengefasst: Industrie 4.0) und die damit einhergehende neuartige Komplexität der Arbeitswelt zu meistern. Bitte gehen Sie im Folgenden von einem Mechatroniker **direkt nach der Ausbildung ohne weitere Berufserfahrung aus,** den Sie neu einstellen würden.

Die **Mindestausprägung der jeweiligen Kompetenz** beschreibt das Kompetenzlevel, das zur Ausübung der Tätigkeit mindestens notwendig ist, um die Herausforderungen durch Industrie 4.0 in den relevanten Prozessen **zufriedenstellend** zu meistern. Die **optimale Ausprägung der Kompetenz** beschreibt das Kompetenzlevel, das für die **bestmögliche** Durchführung der relevanten Prozesse notwendig ist.

Stellen Sie sich vor, dass Ihnen zusätzlich zum Brutto-Monatsgrundgehalt, das Sie dem Mechatroniker zahlen würden, ein monatliches **Gehaltsbudget von 1000 Euro** zur Verfügung steht, das Sie nach Kompetenz und der jeweiligen Ausprägung der Kompetenzen verteilen können. Sie zeigen damit, wieviel es Ihnen wert ist, dass der neu einzustellende Mechatroniker in den jeweiligen Ausprägungen über die unterschiedlichen Kompetenzen verfügt.

Von den 1000 Euro Gehaltsbudget können Sie bis zu 500 Euro beliebig auf die **Mindestausprägung** verschiedener Kompetenzen eines neu einzustellenden Mechatronikers verteilen. Sie geben damit an, wie viel es Ihnen wert ist, dass der Mitarbeiter die jeweilige **Kompetenz in der Mindestausprägung** sicher hat, um die Anforderungen zur Bewältigung der neuen **Herausforderungen durch Industrie 4.0** auf einem **Mindestmaß** zu erfüllen.

Die restlichen 500 Euro des Gehaltsbudgets können Sie beliebig auf die **optimale Ausprägung** verschiedener Kompetenzen eines neu einzustellenden Mechatronikers verteilen. Sie geben damit an, wie viel es Ihnen wert ist, dass der Mitarbeiter die jeweilige **Kompetenz in der optimalen Ausprägung über die Mindestausprägung hinaus hat (also die Differenz von der Mindestausprägung zur optimalen Ausprägung)**, um die Anforderungen zur Bewältigung der neuen **Herausforderungen durch Industrie 4.0 optimal** zu erfüllen.

Warum 1000 Euro Gehaltsbudget?
Das Gehaltsbudget beträgt 1000 Euro und ist circa die maximale Gehaltsdifferenz, die bei Mechatronikern in Deutschland direkt nach der Ausbildung auftritt.

Zurück Weiter

57%

Im Folgenden möchten wir Sie bitten Kompetenzen zu bewerten. Die Bewertung erfolgt im Hinblick auf die Entwicklungen im Bereich Industrie 4.0 für das Berufsbild des Mechatronikers. Mechatroniker haben Aufgaben in folgenden fachlichen Kernbereichen:

- Elektromechanik
- Elektronik
- Elektrotechnik
- Hardwareinstallation
- Softwareinstallation
- Industrieelektronik
- Informationstechnik
- Computertechnik
- Mechatronik
- Montage

Wie komplex ist das Arbeitsfeld eines Mechatronikers in Ihrem Unternehmen im Durchschnitt?
Falls in Ihrem Unternehmen keine Mechatroniker beschäftigt werden, kreuzen Sie bitte "trifft nicht zu" an. Fahren Sie bitte auch bei "trifft nicht zu" mit der Beantwortung des Fragebogens fort. Ihre Meinung als Industrieexperte ist uns sehr wichtig!

sehr wenig komplex				sehr komplex	trifft nicht zu
○	○	○	○	○	○

Zurück Weiter

71%

Nachfolgend finden Sie vier Beispiele mit fiktiven Zahlen für die Bewertung der Kompetenzen sowie der jeweiligen Kompetenzausprägungen zur Erläuterung:

Beispiel 1: Ihnen ist **weder** die Mindestausprägung **noch** die optimale Ausprägung ein **zusätzliches monatliches Gehalt** wert und Sie sehen in beiden Ausprägungen keinen geldwerten zusätzlichen Nutzen.

Verbleibendes Budget	500 €	500 €
Kompetenzausprägung	Mindest-ausprägung	Optimale Ausprägung
Kompetenz A *„Beschreibung Kompetenz A"*	0 €	0 €

*In diesem Beispiel würden Sie dem Mechatroniker für keine der Kompetenzausprägungen ein **zusätzliches monatliches Gehalt** zahlen, d.h., diese Kompetenz stellt **weder in der Mindestausprägung noch** in der **optimalen Ausprägung** einen geldwerten zusätzlichen Nutzen für Sie dar.*

Beispiel 2: Ihnen ist **nur die Mindestausprägung**, jedoch **nicht** die **optimale Ausprägung,** ein **zusätzliches monatliches Gehalt** wert, d.h., Sie erachten die Mindestausprägung für wichtig, aber Sie sehen keinen geldwerten zusätzlichen Nutzen in der optimalen Ausprägung.

Verbleibendes Budget	470 €	500 €
Kompetenzausprägung	Mindest-ausprägung	Optimale Ausprägung
Kompetenz B *„Beschreibung Kompetenz B"*	30 €	0 €

*In diesem Beispiel würden Sie dem Mechatroniker nur für die **Mindestausprägung** der Kompetenz ein **zusätzliches monatliches Gehalt von 30 €** zahlen. Die optimale Ausprägung der Kompetenz stellt keinen geldwerten zusätzlichen Nutzen gegenüber der Mindestausprägung dar.*

Beispiel 3: Ihnen ist **nur die optimale Ausprägung ein zusätzliches monatliches Gehalt wert,** d.h., Sie erachten nur die optimale Ausprägung für wichtig, aber Sie sehen keinen geldwerten zusätzlichen Nutzen nur in der Mindestausprägung.

Verbleibendes Budget	500 €	470 €
Kompetenzausprägung	Mindest-ausprägung	Optimale Ausprägung
Kompetenz C *„Beschreibung Kompetenz C"*	0 €	30 €

*In diesem Beispiel stellt die Mindestausprägung der Kompetenz keinen geldwerten zusätzlichen Nutzen dar. Sie würden dem Mechatroniker aber für die **optimale Ausprägung** der Kompetenz ein **zusätzliches monatliches Gehalt von 30 €** zahlen.*

Beispiel 4: Ihnen ist **sowohl** die **Mindestausprägung** als **auch** die **optimale Ausprägung** ein **zusätzliches monatliches Gehalt** wert und Sie sehen einen geldwerten zusätzlichen Nutzen in beiden Ausprägungen.

Verbleibendes Budget	470 €	470 €
Kompetenzausprägung	Mindest-ausprägung	Optimale Ausprägung
Kompetenz D *„Beschreibung Kompetenz D"*	30 €	30 €

*In diesem Beispiel würden Sie dem Mechatroniker für die **Mindestausprägung** der Kompetenz ein **zusätzliches monatliches Gehalt von 30 €** zahlen. Wenn der Mechatroniker statt der Mindestausprägung auch noch über **die optimale Ausprägung** der Kompetenz verfügt, würden Sie **darüber hinaus ein zusätzliches monatliches Gehalt von 30 €** zahlen. Insgesamt zahlen Sie dem Mechatroniker somit ein **zusätzliches monatliches Gehalt von 60 €** und beide Ausprägugen haben für Sie einen geldwerten zusätzlichen Nutzen.*

Zurück Weiter

86%

Sie haben im Folgenden ein zusätzliches monatliches Gehaltsbudget in Höhe von 1000 Euro für einen neu einzustellenden Mechatroniker zur Verfügung:

Von den 1000 Euro Gehaltsbudget können Sie bis zu 500 Euro beliebig auf die **Mindestausprägung** verschiedener Kompetenzen eines neu einzustellenden Mechatronikers verteilen. Sie geben damit an, wie viel es Ihnen wert ist, dass der Mitarbeiter die jeweilige **Kompetenz in der Mindestausprägung sicher** hat, um die Anforderungen zur Bewältigung der neuen **Herausforderungen durch Industrie 4.0 auf einem Mindestmaß** zu erfüllen.

Die restlichen 500 Euro des Gehaltsbudgets können Sie beliebig auf die **optimale Ausprägung** verschiedener Kompetenzen eines neu einzustellenden Mechatronikers verteilen. Sie geben damit an, wie viel es Ihnen wert ist, dass der Mitarbeiter die jeweilige **Kompetenz in der optimalen Ausprägung über die Mindestausprägung hinaus hat** (also die **Differenz von der Mindestausprägung zur optimalen Ausprägung**), um die Anforderungen zur Bewältigung der neuen **Herausforderungen durch Industrie 4.0** optimal zu erfüllen.

Sie können für die jeweilige Ausprägung (Mindest vs. Optimal) auch eine kleinere Summe als 500 Euro auf die einzelnen Kompetenzen verteilen. **Es muss in jedem Textfeld eine Zahl stehen** (mindestens eine Null). Die Definition für Mindestausprägung und optimale Ausprägung sehen Sie auch nochmal, wenn Sie den Mauszeiger kurz auf dem rot eingekreisten Fragezeichen unter dem entsprechenden Begriff ruhen lassen.

Verbleibendes Budget	**500 €**	**500 €**
Kompetenzausprägung	Mindest-ausprägung ?	Optimale Ausprägung ?
Zuverlässigkeit Zuverlässig, verantwortungsbewusst und verlässlich zu sein sowie seine Verpflichtungen zu erfüllen.	€	€
Analytisches Denkvermögen Informationen zu analysieren und logisch zu denken, um arbeitsbezogene Themen und Probleme zu bearbeiten.	€	€
Anpassungsfähigkeit/Flexibilität Offen für (positive und negative) Veränderungen sowie für die möglichen vielfältigen Aufgaben eines Arbeitsplatzes zu sein.	€	€
Kooperationsvermögen Freundlich im Umgang mit Mitmenschen und eine freundliche, kooperative Haltung ausstrahlen.	€	€
Problemlösungskompetenz Identifizieren von komplexen Problemen und Bewerten von problembezogenen Informationen, um Handlungsmöglichkeiten zu entwickeln sowie Abwägung von Optionen und Implementierung von Lösungen.	€	€
Systemanalyse und -verständnis Festlegung, wie ein System arbeiten soll und wie Änderungen der Bedingungen im Betrieb und der Umwelt die Ergebnisse beeinflussen.	€	€
Aktives Lernen Verständnis für die Auswirkungen von neuen Informationen für aktuelle und zukünftige Problemlösungen und Entscheidungen.	€	€
Troubleshooting Ermittlung von Fehlerursachen in der Produktion und Entscheidung, was zu tun ist, um den Fehler zu lösen.	€	€
Problemsensitivität Fähigkeit, zu erkennen, wenn etwas falsch ist oder wahrscheinlich schief geht. Dies beinhaltet nicht das Lösen des Problems, sondern nur das Erkennen, dass ein Problem vorliegt.	€	€
Induktive Schlussfolgerung Fähigkeit, verschiedene Informationen miteinander zu kombinieren, um allgemeingültige Regeln oder Schlussfolgerungen zu bilden (Beinhaltet auch das Auffinden von Beziehungen zwischen scheinbar zusammenhangslosen Ereignissen).	€	€
Deduktive Schlussfolgerung Fähigkeit, allgemeingültige Regeln auf spezifische Probleme anzuwenden, um sinnvolle Lösungen zu erhalten.	€	€
Strukturieren von Informationen Fähigkeit, Dinge oder Aktionen in einer bestimmten Reihenfolge oder nach einem Muster anzuordnen, das spezifischen Regeln oder einem Set von Regeln folgt (z.B. Zahlenmuster, Briefe, Wörter, Bilder, mathematische Rechnungen).	€	€
Kenntnisse im Bereich Computer und Elektronik Kenntnisse von Schaltkreisen, Prozessoren, Chips, elektronischem Equipment und Computer Hard- und Software einschließlich Anwendungen und Programmieren.	€	€
Kenntnisse im Bereich Mechanik Mechanisches Wissen über Maschinen und Werkzeuge inklusive deren Design, Nutzung, Reparatur und Instandhaltung.	€	€
Kenntnisse im Bereich Maschinenbau und Technologie Wissen über die praktische Anwendung des Maschinenbaus und von entsprechenden Technologien. Dies beinhaltet Prinzipien, Technik, Beschreibungen und Ausrüstung für das Design und die Produktion von verschiedenen Gütern und Serviceleistungen.	€	€
Kenntnisse im Bereich Elektrotechnik Elektrotechnisches Wissen von Maschinen und Werkzeugen, inklusive deren Design, Nutzung, Reparatur und Instandhaltung.	€	€

Zurück Weiter

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100%

Sie haben folgende Kompetenzen in der **Mindestausprägung mit 0** bewertet. Bitte geben Sie kurz den **Grund** an!

Kenntnisse im Bereich Maschinenbau und Technologie ?

- Diese Kompetenz hat in der jeweiligen Ausprägung keinen geldwerten zusätzlichen Nutzen.
- Diese Kompetenz ist in der jeweiligen Ausprägung eine Grundvoraussetzung für die Einstellung und wird deshalb von jedem erwartet und ist kein zusätzliches Gehalt wert.
- Sonstiges

Kenntnisse im Bereich Elektrotechnik ?

- Diese Kompetenz hat in der jeweiligen Ausprägung keinen geldwerten zusätzlichen Nutzen.
- Diese Kompetenz ist in der jeweiligen Ausprägung eine Grundvoraussetzung für die Einstellung und wird deshalb von jedem erwartet und ist kein zusätzliches Gehalt wert.
- Sonstiges

Sie haben folgende Kompetenzen in der **optimalen Ausprägung mit 0** bewertet. Bitte geben Sie kurz den **Grund** an!

Kenntnisse im Bereich Maschinenbau und Technologie ?

- Diese Kompetenz hat in der jeweiligen Ausprägung keinen geldwerten zusätzlichen Nutzen.
- Diese Kompetenz ist in der jeweiligen Ausprägung eine Grundvoraussetzung für die Einstellung und wird deshalb von jedem erwartet und ist kein zusätzliches Gehalt wert.
- Sonstiges

Kenntnisse im Bereich Elektrotechnik ?

- Diese Kompetenz hat in der jeweiligen Ausprägung keinen geldwerten zusätzlichen Nutzen.
- Diese Kompetenz ist in der jeweiligen Ausprägung eine Grundvoraussetzung für die Einstellung und wird deshalb von jedem erwartet und ist kein zusätzliches Gehalt wert.
- Sonstiges

Weiter

100%

Vielen Dank für Ihre Teilnahme und Ihre wertvolle Zeit!

Wichtiger Hinweis:
Falls Sie weiterführende Informationen über die Studienergebnisse wünschen, klicken Sie auf folgenden Link und wir übersenden Ihnen dann nach Auswertung der Studie einen Abschlussbericht. Die Adresse wird mittels einer separaten Umfrage unabhängig von Ihren angegebenen Daten gespeichert, um die Anonymität der Umfrage zu gewährleisten.

Link zur E-Mail-Adressen-Abfrage

Kommen Sie bei Fragen gerne auf uns zu (schinner@controlling.rwth-aachen.de).

Wir bedanken uns für Ihre Unterstützung!

Mit freundlichen Grüßen

Prof. Dr. Robert Böhm (Lehrstuhl für Decision Analysis, RWTH Aachen University),
Prof. Dr. Peter Letmathe (Lehrstuhl für Controlling, RWTH Aachen University),
Dipl. Kfm. Matthias Schinner (Lehrstuhl für Controlling, RWTH Aachen University)

Appendix III–6: Main Survey – (Translated Version; in English)

14%

Dear Sir or Madam,

at RWTH Aachen University, we are conducting a scientific study on the topic of **"The value of competencies in the age of Industry 4.0."** The aim of the study is to investigate which **competencies will be needed by mechatronics technicians* in the future** in order to master the new technological challenges posed by connectivity, automation and the digitization of manufacturing and the associated complexity of the world of work. For this purpose, we interview managers from **human resources** and **production management**. As an expert, you will help to develop implications for the **training of young people** and thus better prepare them for the new world of work.

We would be very pleased if you could take **5-10 minutes** to complete the following questionnaire. In return, we will be happy to send you the detailed r**esults of the study** exclusively before publication. If you are interested, please enter your e-mail address in a separate survey at the end of the questionnaire so that your anonymity is still ensured (all information will be treated strictly confidentially).

You can pause answering the questionnaire at any time and continue at a later time. You can use the link from the e-mail to return as often as you like until the questionnaire is completed and thus continue answering again.

If you have any questions, you are of course welcome to contact us using the details below.

We thank you for your support and appreciate your time very much!

Kind regards

Prof. Dr. Robert Böhm
Prof. Dr. Peter Letmathe
Dipl. Kfm. Matthias Schinner

Correspondence address:
Chair of Management Accounting, RWTH Aachen University – Matthias Schinner – schinner@controlling.rwth-aachen.de

*For reasons of better readability, the simultaneous use of masculine and feminine forms of language has been avoided. All references to persons nevertheless apply to both genders.

Continue

29%

All information you provide here is voluntary!

Please specify your gender.

- Male
- Female
- Other

Please indicate your function in the company.

- Human Resources Manager / Personnel Management
- Production Manager / Production Management
- Working in both functions
- Other:

Please indicate your age (as a whole number).

Years

Please indicate your highest level of education.

- No degree
- Elementary / Main School
- Middle School Diploma
- (Technical) Baccalaureate
- Completed Vocational Training
- Master Craftman´s Certificate
- Bachelor
- Master
- Diploma
- PhD

Please indicate your total work experience in year (as a whole number)

Years

Please indicate your current position within the company.
If none of the suggested answer choices apply, please be as specific as possible about your position.

- Clerk
- Subject Specialist
- Group Leader
- Team Leader
- Head of Department
- Area Manager
- Managing Director
- Other:

Back Continue

43%

Task description:
The following competencies were selected by experts for this study and are of particular importance for the **job profile of the mechatronics technician** in order to master the new technological challenges posed by networking, automation as well as digitalization of production (summarized: Industry 4.0) and the associated new type of complexity in the world of work. In the following, please assume that you would hire a mechatronics technician **directly after training without further work experience**.

The **minimal level of the respective competency** describes the level of competency required to perform the activity in order to **adequately** meet the challenges posed by Industrie 4.0 in the relevant processes. The **optimal level of competency** describes the level of competence required for the **best possible** performance of the relevant processes.

Imagine that, in addition to the gross monthly base salary that you would pay the mechatronics engineer, you have a monthly salary **budget of 1000** euros that you can distribute according to competency and the respective level of the competencies. In this way, you show how much it is worth to you that the mechatronics engineer, whom you plan to hire, has the various competencies in the respective levels of competency.

You can allocate up to 500 euros of the 1000 euro salary budget as you wish to the **minimal level** of various competencies of a newly hired mechatronics technician. In this way, you indicate how much it is worth to you that the employee has the respective **competency at the minimal level** in order to meet the requirements for mastering the new **challenges posed by Industry 4.0** at a **minimal level**.

You can allocate the remaining 500 euros of the salary budget as you wish to the **optimal level** of various competencies of a new mechatronics engineer who you intend to hire. In this way, you indicate how much it is worth to you for the employee to have the respective **competency in the optimal level above the minimal level (i.e., the difference between the minimal level and the optimal level)** in order to optimally meet the requirements for mastering the new **challenges posed by Industry 4.0**.

Why 1000 Euro salary budget?
The salary budget is 1000 euros and is approximately the maximum salary difference that occurs for mechatronics engineers in Germany directly after training.

Back Continue

57%

In the following, we would like to ask you to evaluate competencies. The assessment is made with regard to the developments in the field of Industry 4.0 for the job profile of the mechatronics technician. Mechatronics technicians have tasks in the following core technical areas:

- Electromechanics
- Electronics
- Electrical engineering
- Hardware installation
- Software installation
- Industrial electronics
- Information technology
- Computer technology
- Mechatronics
- Assembly

On the average, how complex is the field of mechatronics technician in your company?
If your company does not employ mechatronics engineers, please check "does not apply". Please continue answering the questionnaire even if "does not apply". Your opinion as an industry expert is very important to us!

not very complex				very complex	does not apply
○	○	○	○	○	○

Back Continue

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71%

Below you will find four examples with fictitious numbers for the evaluation of the competencies as well as the respective competency proficiencies for explanation:

Example 1: Neither the minimal level of competency **nor** the optimal level of competency is worth an **additional monthly salary** to you, and you do not see any additional monetary benefit in either level of competency.

Remaining Budget	**500 €**	**500 €**
Level of competency	minimal level	optimal level
Competency A *„Description Competency A"*	0 €	0 €

*In this example, you would not pay the mechatronics technician **an additional monthly salary** for any of the competency levels, i.e., this competency does not represent a **monetary additional benefit** for you at either the **minimal level** or the **optimal level**.*

Example 2: Only **the minimal level,** but **not the optimal level**, is worth an **additional monthly salary** to you, i.e. you consider the minimal level to be important, but you do not see any additional monetary benefit in the optimal level.

Remaining Budget	**470 €**	**500 €**
Level of competency	minimal level	optimal level
Competency B *„Description Competency B"*	30 €	0 €

*In this example, you would only pay the mechatronics engineer an **additional monthly salary of €30** for the **minimal level** of the competency. The optimal competency level does not represent a monetary additional benefit compared to the minimal competency level.*

Example 3: Only the **optimal proficiency** is worth an **additional monthly salary** to you, i.e. you only consider the optimal proficiency important, whereas you do not see additional monetary benefits in only the minimal proficiency.

Remaining Budget	**500 €**	**470 €**
Level of competency	minimal level	optimal level
Competency C *„Description Competency C"*	0 €	30 €

*In this example, the minimal level of competency does not represent a monetary additional benefit. However, you would pay the mechatronics engineer an **additional monthly salary of €30** for the **optimal level of the competency.***

Example 4: Both the **minimal level and** the **optimal level** are worth an **additional monthly salary** to you and you see a monetary additional benefit in both levels.

Remaining Budget	**470 €**	**470 €**
Level of competency	minimal level	optimal level
Competency D *„Description Competency D"*	30 €	30 €

*In this example, you would pay the mechatronics engineer an **additional monthly salary of €30** for the **minimal level of competency**. If the mechatronics technician also has the **optimal level of competency** instead of the minimal level, you would **also pay an additional monthly salary of €30.** In total, you would pay the mechatronics technician an **additional monthly salary of €60** and both levels have an additional monetary benefit for you.*

Back | Continue

86%

In the following, you have an additional monthly salary budget of 1000 euros available for a newly hired mechatronics technician:

You can allocate up to 500 euros of the 1000 euro salary budget as you wish to the **minimal level** of various competencies of a new mechatronics technician whom you wish to hire. In this way, you indicate how much it is worth to you that the employee has the respective **competency at the minimal level** of proficiency in order to meet the requirements for mastering the new **challenges posed by Industry 4.0 at a minimal level**.

You can allocate the remaining 500 euros of the salary budget as you wish to the **optimal - level** , of various competencies of a newly hired mechatronics engineer. In this way, you indicate how much it is worth to you for the employee to have the respective **competency at the optimal level above the minimal level** (i.e., the difference between the minimal level and the optimal level) in order to fulfill the requirements for mastering the new**challenges posed by Industry 4.0** in the best possible way.

You can also allocate a smaller sum than 500 euros to the individual competencies for the respective proficiency (minimal vs. optimal). **There must be a number in each text field (at least a zero)**. You can also see the definition for minimal and optimal proficiency again by briefly resting the cursor on the question mark circled in red under the corresponding term.

Verbleibendes Budget	**500 €**	**500 €**
Level of competency	minimal level ?	optimal level ?
Dependability Job requires being reliable, responsible, and dependable, and fulfilling obligations.	€	€
Analytical Thinking Job requires analyzing information and using logic to address work-related issues and problems.	€	€
Adaptability/Flexibility Job requires being open to change (positive or negative) and to considerable variety in the workplace.	€	€
Cooperation Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude.	€	€
Complex Problem-Solving Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	€	€
Systems Analysis Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	€	€
Active Learning Understanding the implications of new information for both current and future problem-solving and decision-making.	€	€
Troubleshooting Determining causes of operating errors and deciding what to do about it.	€	€
Problem sensitivity The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem.	€	€
Inductive Reasoning The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).	€	€
Deductive Reasoning The ability to apply general rules to specific problems to produce answers that make sense.	€	€
Information Ordering The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g. patterns of numbers, letters, words, pictures, mathematical operations).	€	€
Computers & Electronics Knowledge Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.	€	€
Mechanical Knowledge Knowledge of machines and tools, including their designs, uses, repair, and maintenance.	€	€
Engineering and Technology Knowledge Knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services.	€	€
Electrical Engineering Knowledge Electrotechnical knowledge of machines and tools, including their designs, uses, repair, and maintenance.	€	€

Back Continue

100%

You have rated the following competencies as **0 at the minimal proficiency level**. Please briefly state the **reason**.

Engineering and Technology Knowledge

- This competency has no added monetary value in its respective manifestation.
- This competency, in its respective level, is a basic requirement for employment and is therefore expected of everyone and is not worth an additional salary.
- Others

Electrical Engineering Knowledge

- This competency has no added monetary value in its respective manifestation.
- This competency, in its respective level, is a basic requirement for employment and is therefore expected of everyone and is not worth an additional salary.
- Others

You have rated the following competencies as **0 at the optimal proficiency level**. Please briefly state the **reason**.

Engineering and Technology Knowledge

- This competency has no added monetary value in its respective manifestation.
- This competency, in its respective level, is a basic requirement for employment and is therefore expected of everyone and is not worth an additional salary.
- Others

Electrical Engineering Knowledge

- This competency has no added monetary value in its respective manifestation.
- This competency, in its respective level, is a basic requirement for employment and is therefore expected of everyone and is not worth an additional salary.
- Others

Continue

100%

Thank you for your participation and valuable time!

Important notice:

If you would like further information about the results of this study, click on the following link and we will send you a final report after evaluating the study. The address will be stored by means of a separate survey, independent of the data you have provided, in order to guarantee the anonymity of the survey.

Link to email address query

Feel free to contact us with any questions (schinner@controlling.rwth-aachen.de).

We thank you for your support!

With kind regards

Prof. Dr. Robert Böhm (Chair of Decision Analysis, RWTH Aachen University),
Prof. Dr. Peter Letmathe (Chair of Management Accounting, RWTH Aachen University),
Dipl. Kfm. Matthias Schinner (Chair of Management Accounting, RWTH Aachen University)

Appendix III–7: Expert Survey (Original Version; in German)

13%

Sehr geehrte Damen und Herren,

wir planen eine wissenschaftliche Studie zum Thema „Wert von Kompetenzen im Zeitalter von Industrie 4.0“. Ziel der Studie ist es, zu untersuchen, welche Kompetenzen in Zukunft von Mechatronikern/Mechatronikerinnen benötigt werden, um die neuen technologischen Herausforderungen durch Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende Komplexität der Arbeitswelt zu meistern.

Dafür haben wir Sie – als einen von 7 Experten/Expertin aus der Industrie – für diese Vorstudie ausgewählt, um eine Vorauswahl von in der Literatur aufgeführten Kompetenzen für die Hauptstudie zu treffen. Dazu bitten wir Sie die voraussichtliche Wichtigkeit der aufgeführten Kompetenzen für das Berufsbild Mechatroniker/Mechatronikerin auf einer vorgegebenen Skala anzugeben. Ihre Auswahl soll zu einer Selektion der 16 wichtigsten Kompetenzen für die Zukunft in dem Berufsbild Mechatroniker/Mechatronikerin führen.

Wir würden uns ausgesprochen freuen, wenn Sie sich 10 Minuten Zeit nehmen, um den folgenden Fragebogen auszufüllen. Als Dank lassen wir Ihnen gerne die detaillierten Ergebnisse der Hauptstudie exklusiv vor der Veröffentlichung zukommen. Bei Interesse geben Sie dazu bitte am Ende des Fragebogens Ihre E-Mail-Adresse an.

Die Teilnahme an der Befragung erfolgt ansonsten natürlich anonym. Sie können die Beantwortung des Fragebogens jederzeit unterbrechen und zu einem späteren Zeitpunkt fortfahren.

Bei Fragen können Sie uns unter den unten angegebenen Kontaktdaten erreichen.

Wir bedanken uns im Voraus für Ihre Unterstützung!

Mit freundlichen Grüßen

Prof. Dr. Robert Böhm
Prof. Dr. Peter Letmathe
Dipl. Kfm. Matthias Schinner

Korrespondenzadresse: Lehrstuhl für Controlling, RWTH Aachen University – Matthias Schinner – schinner@controlling.rwth-aachen.de

Weiter

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25%

Die Bewertung der Kompetenzen erfolgt im Hinblick auf die Entwicklungen im Bereich Industrie 4.0 für das Berufsbild Mechatroniker/Mechatronikerin. Anbei finden Sie eine kurze Beschreibung des Tätigkeitsbereichs von Mechatronikern/Mechatronikerinnen:

Mechatroniker/Mechatronikerinnen arbeiten in der Montage und Instandhaltung von komplexen Maschinen, Anlagen und Systemen im Anlagen- und Maschinenbau bzw. bei den Abnehmern und Betreibern dieser mechatronischen Systeme.
Mechatroniker/Mechatronikerinnen üben ihre Tätigkeiten an unterschiedlichen Einsatzorten, vornehmlich auf Montagebaustellen, in Werkstätten oder im Servicebereich, unter Beachtung der einschlägigen Vorschriften und Sicherheitsbestimmungen selbständig nach Unterlagen und Anweisungen aus. Dabei arbeiten sie häufig im Team. Sie stimmen ihre Arbeit mit vor- und nachgelagerten Bereichen ab.
Mechatroniker/Mechatronikerinnen sind im Sinne der Unfallverhütungsvorschriften Elektrofachkräfte.

Fachliche Kernbereiche:
- Elektromechanik
- Elektronik
- Elektrotechnik
- Hardwareinstallation
- Softwareinstallation
- Industrieelektronik
- Informationstechnik
- Computertechnik
- Mechatronik
- Montage

Im Anschluss kommen Sie direkt zu einer Auswahl verschiedener in der Literatur beschriebener Kompetenzen, die häufig genannt werden. Bitte bewerten Sie diese nach ihrer voraussichtlichen Wichtigkeit für das Berufsbild Mechatroniker/Mechatronikerin, um die neuen technologischen Herausforderungen durch Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende neuartige Komplexität der Arbeitswelt, die in Zukunft entsteht, zu meistern.

Zurück | Weiter

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38%

Die Arbeitswelt innerhalb von Produktionsuntemehmen wird sich in den nächsten Jahren stark durch neue technologische Trends verändern. Bitte bewerten Sie daher die voraussichtliche Wichtigkeit der folgenden Kompetenzen für die Leistungsfähigkeit von Mechatronikern/Mechatronikerinnen, um die neuen technologischen Herausforderungen im Rahmen der Entwicklungen von Industrie 4.0, wie z.B. Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende neuartige Komplexität der Arbeitswelt zu meistern.

Im Folgenden finden Sie den Namen der zu bewertenden Kompetenz sowie eine kurze Beschreibung.

Mathematikkenntnisse
Kenntnisse der Arithmetik, Algebra, Geometrie, Analysis, Statistik und deren Anwendung.

Wie wichtig sind Mathematikkenntnisse für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Elektrotechnik
Elektrotechnisches Wissen von Maschinen und Werkzeugen, inklusive deren Design, Nutzung, Reparatur und Instandhaltung.

Wie wichtig sind Kenntnisse im Bereich Elektrotechnik für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Design
Wissen über Designtechniken, Werkzeuge und Prinzipien bei der Erstellung von präzisen technischnen Plänen, Blaupausen, Zeichnungen und Modellen.

Wie wichtig sind Kenntnisse im Bereich Design für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Mechanik
Mechanisches Wissen über Maschinen und Werkzeuge inklusive deren Design, Nutzung, Reparatur und Instandhaltung.

Wie wichtig sind Kenntnisse im Bereich Mechanik für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Englischkenntnisse
Wissen über die Struktur und den Inhalt der englischen Sprache, einschließlich der Bedeutung und der Rechtschreibung von Wörtern, Regeln zum Aufbau von Aufsätzen und der jeweiligen Grammatik.

Wie wichtig sind Englischkenntnisse für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Maschinenbau und Technologie
Wissen über die praktische Anwendung des Maschinenbaus und von entsprechenden Technologien. Das beinhaltet Prinzipien, Technik, Beschreibungen und Ausrüstung für das Design und die Produktion von verschiedenen Gütern und Serviceleistungen.

Wie wichtig sind Kenntnisse im Bereich Maschinenbau und Technologie für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Computer & Elektronik
Kenntnisse von Schaltkreisen, Prozessoren, Chips, elektronischem Equipment und Computer Hard- und Software einschließlich Anwendungen und Programmieren.

Wie wichtig sind Kenntnisse im Bereich Computer & Elektronik für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Kundenservice
Wissen über Prinzipien und Prozesse, um individuellen Service und Kundenservice zu bieten. Dies beinhaltet das ermitteln der Kundenbedürfnisse, Qualitätsstandards einzuhalten und die Kundenzufriedenheit einschätzen zu können.

Wie wichtig sind Kenntnisse im Bereich Kundenservice für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Bildung & Training
Kenntnisse von Prinzipien und Methoden für Kurs- und Trainingsgestaltung, Lehre und Anleitung von Einzelnen und Gruppen und das Beurteilen von Trainingserfolgen.

Wie wichtig sind Kenntnisse im Bereich Bildung & Training für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Kenntnisse im Bereich Produktion und Verarbeitung
Wissen über Rohstoffe, Produktionsprozesse, Arten der Qualitätskontrolle, Kosten und andere Techniken, um die Effektivität der Produktion sowie der Distribution der Güter zu maximieren.

Wie wichtig sind Kenntnisse im Bereich Produktion & Verarbeitung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

Unwichtig | Weniger Wichtig | Neutral | Wichtig | Sehr Wichtig

Zurück | Weiter

50%

Die Arbeitswelt innerhalb von Produktionsunternehmen wird sich in den nächsten Jahren stark durch neue technologische Trends verändern. Bitte bewerten Sie daher die voraussichtliche Wichtigkeit der folgenden Kompetenzen für die Leistungsfähigkeit von Mechatronikern/Mechatronikerinnen, um die neuen technologischen Herausforderungen im Rahmen der Entwicklungen von Industrie 4.0, wie z.B. Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende neuartige Komplexität der Arbeitswelt zu meistern.

Im Folgenden finden Sie den Namen der zu bewertenden Kompetenz sowie eine kurze Beschreibung.

Selbstständigkeit
Für den Beruf ist es notwenig eigenständig zu arbeiten, sich selbst, auch mit wenig Führung durch Vorgesetzte, anzuleiten und Dinge eigenständig umzusetzen.

Wie wichtig ist die Kompetenz Selbstständigkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Ausdauer
Für den Beruf ist Ausdauer beim Auftreten von Hindernissen notwendig.

Wie wichtig ist die Kompetenz Ausdauer für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Kooperationsvermögen
Für den Beruf ist es notwendig, freundlich im Umgang mit Mitmenschen zu sein und eine freundliche, kooperative Haltung auszustrahlen.

Wie wichtig ist die Kompetenz Kooperationsvermögen für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Initiative
Für den Beruf ist es notwendig, Verantwortung zu übernehmen und sich Herausforderungen zu stellen.

Wie wichtig ist die Kompetenz Initiative für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Detailgenauigkeit
Für den Beruf ist es notwendig, auf Details zu achten und sorgfältig bei der Bearbeitung von Aufgaben zu sein.

Wie wichtig ist die Kompetenz Detailgenauigkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Innovationskompetenz
Für den Beruf ist Kreativität und alternatives Denken notwendig, um neue Ideen und Antworten auf arbeitsbezogene Fragen zu finden.

Wie wichtig ist die Kompetenz Innovationskompetenz für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Stresstoleranz
Für den Beruf ist es notwendig, Kritik zu vertragen und ruhig und zielgerichtet mit Stresssituationen umzugehen.

Wie wichtig ist die Kompetenz Stresstoleranz für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Anpassungsfähigkeit/Flexibilität
Für den Beruf ist es notwendig, offen für (positive und negative) Veränderungen sowie für die möglichen vielfältigen Aufgaben eines Arbeitsplatzes zu sein.

Wie wichtig ist die Kompetenz Anpassungsfähigkeit/Flexibilität für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Selbstbeherrschung
Für den Beruf ist es notwendig, die Fassung zu wahren, seine Emotionen wie Wut unter Kontrolle zu behalten, und aggressives Verhalten auch in schwierigen Situationen zu vermeiden.

Wie wichtig ist die Kompetenz Selbstbeherrschung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Zuverlässigkeit
Für den Beruf ist es notwendig, zuverlässig, verantwortungsbewusst, verlässlich zu sein sowie Verpflichtungen zu erfüllen.

Wie wichtig ist die Kompetenz Zuverlässigkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Analytisches Denkvermögen
Für den Beruf ist es notwendig, Informationen zu analysieren und logisch zu denken, um arbeitsbezogene Themen und Probleme zu bearbeiten.

Wie wichtig ist die Kompetenz Analytisches Denkvermögen für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Zurück Weiter

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63%

Die Arbeitswelt innerhalb von Produktionsunternehmen wird sich in den nächsten Jahren stark durch neue technologische Trends verändern. Bitte bewerten Sie daher die voraussichtliche Wichtigkeit der folgenden Kompetenzen für die Leistungsfähigkeit von Mechatronikern/Mechatronikerinnen, um die neuen technologischen Herausforderungen im Rahmen der Entwicklungen von Industrie 4.0, wie z.B. Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende neuartige Komplexität der Arbeitswelt zu meistern.

Im Folgenden finden Sie den Namen der zu bewertenden Kompetenz sowie eine kurze Beschreibung.

Kritisches Denken
Der Gebrauch von logischem und vernünftigem Denken zur Identifizierung von Vor- und Nachteilen alternativer Lösungen, Schlussfolgerungen oder Lösungsansätzen für Probleme.

Wie wichtig ist die Kompetenz Kritisches Denken für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Lernstrategien
Situationsadäquate Auswahl und Nutzung von Trainingsmethoden und Prozeduren, um neue Dinge zu lernen oder zu lehren.

Wie wichtig ist die Kompetenz Lernstrategien für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Problemlösungskompetenz
Identifizieren von komplexen Problemen und Bewerten von problembezogenen Informationen, um Handlungsmöglichkeiten zu entwickeln und Abwägung von Optionen und Implementierung von Lösungen.

Wie wichtig ist die Kompetenz Problemlösungskompetenz für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Systemanalyse und -verständnis
Festlegung, wie ein System arbeiten soll und wie Änderungen der Bedingungen, im Betrieb und der Umwelt die Ergebnisse beeinflussen.

Wie wichtig ist die Kompetenz Systemanalyse und -verständnis für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Programmieren
Schreiben von Computerprogrammen für verschiedene Zwecke.

Wie wichtig ist die Kompetenz Programmieren für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Aktives Lernen
Verständnis für die Auswirkungen von neuen Informationen für aktuelle und zukünftige Problemlösungen und Entscheidungen.

Wie wichtig ist die Kompetenz Aktives Lernen für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Urteilsvermögen & Entscheidungsfindung
Berücksichtigung des relativen Nutzens und der relativen Kosten von möglichen Handlungen, um die am besten geeignete Handlung zu wählen.

Wie wichtig ist die Kompetenz Urteilsvermögen & Entscheidungsfindung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Soziale Wahrnehmungsfähigkeit
Reaktionen anderer erkennen und verstehen, warum sich diese so verhalten.

Wie wichtig ist die Kompetenz Soziale Wahrnehmungsfähigkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Troubleshooting
Ermittlung von Fehlerursachen in der Produktion und Entscheidung, was zu tun ist, um den Fehler zu lösen.

Wie wichtig ist die Kompetenz Troubleshooting für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Produktionsüberwachung
Überwachung von Messgeräten, Zifferblättern oder anderen Indikatoren, um sicherzustellen, dass eine Maschine ordnungsgemäß läuft.

Wie wichtig ist die Kompetenz Produktionsüberwachung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Zeitmanagement
Die eigene Zeit und die Zeit anderer einteilen können.

Wie wichtig ist die Kompetenz Zeitmanagement für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Technologiedesign
An die Bedürfnisse von Nutzern ausgerichtete Entwicklung oder Anpassung von Anlagen und Technologie.

Wie wichtig ist die Kompetenz Technologiedesign für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Zurück | Weiter

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Die Arbeitswelt innerhalb von Produktionsunternehmen wird sich in den nächsten Jahren stark durch neue technologische Trends verändern. Bitte bewerten Sie daher die voraussichtliche Wichtigkeit der folgenden Kompetenzen für die Leistungsfähigkeit von Mechatronikern/Mechatronikerinnen, um die neuen technologischen Herausforderungen im Rahmen der Entwicklungen von Industrie 4.0, wie z.B. Vernetzung, Automatisierung sowie Digitalisierung der Produktion und die damit einhergehende neuartige Komplexität der Arbeitswelt zu meistern.

Im Folgenden finden Sie den Namen der zu bewertenden Kompetenz sowie eine kurze Beschreibung.

Problemsensitivität
Fähigkeit, zu erkennen, wenn etwas falsch ist oder wahrscheinlich schief geht. Dies beinhaltet nicht das Lösen des Problems, sondern nur das Erkennen, dass ein Problem vorliegt.

Wie wichtig ist die Kompetenz Problemsensitivität für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Induktive Schlussfolgerung
Fähigkeit, verschiedene Informationen miteinander zu kombinieren, um allgemeingültige Regeln oder Schlussfolgerungen zu bilden. (Beinhaltet auch das Auffinden von Beziehungen zwischen scheinbar zusammenhangslosen Ereignissen).

Wie wichtig ist die Kompetenz Induktive Schlussfolgerung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Mündliches Verstehen
Fähigkeit, zuzuhören und Informationen und Ideen, die von anderen mittels Sprache vorgetragen werden, zu verstehen.

Wie wichtig ist die Kompetenz Mündliches Verstehen für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Strukturieren von Informationen
Fähigkeit, Dinge oder Aktionen in einer bestimmten Reihenfolge oder nach einem Muster anzuordnen, das spezifischen Regeln oder einem Set von Regeln folgt (z.B. Zahlenmuster, Briefe, Wörter, Bilder, mathematische Rechnungen).

Wie wichtig ist die Kompetenz Strukturieren von Informationen für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Selektive Aufmerksamkeit
Fähigkeit, sich auf eine Aufgabe für eine gewisse Zeit zu konzentrieren, ohne dabei abgelenkt zu werden.

Wie wichtig ist die Kompetenz Selektive Aufmerksamkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Leseverständnis
Fähigkeit, zu lesen und Informationen und Ideen in Schriftform zu verstehen.

Wie wichtig ist die Kompetenz Leseverständnis für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Mündliche Ausdrucksweise
Fähigkeit, Informationen und Ideen durch Sprache zu kommunizieren, sodass andere diese verstehen.

Wie wichtig ist die Kompetenz Mündliche Ausdrucksweise für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Deduktive Schlussfolgerung
Fähigkeit, allgemeingültige Regeln auf spezifische Probleme anzuwenden, um sinnvolle Lösungen zu erhalten.

Wie wichtig ist die Kompetenz Deduktive Schlussfolgerung für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Schriftlicher Ausdruck
Fähigkeit, Informationen und Ideen in Schriftform anderen verständlich zu machen.

Wie wichtig ist die Kompetenz Schriftlicher Ausdruck für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Anleitungsfähigkeit
Andere unterrichten wie Dinge gemacht werden.

Wie wichtig ist die Kompetenz Anleitungsfähigkeit für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Mathematisches Denken
Fähigkeit, die richtigen mathematischen Methoden oder Formeln zur Lösung eines Problems zu nutzen.

Wie wichtig ist die Kompetenz Mathematisches Denken für die zukünftige Leistung eines/einer Mechatronikers/Mechatronikerin im Zuge von Industrie 4.0?

○ Unwichtig ○ Weniger Wichtig ○ Neutral ○ Wichtig ○ Sehr Wichtig

Zurück | Weiter

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Vielen Dank für die Teilnahme an unserer Vorstudie zum Thema Wert von Kompetenzen im Zeitalter von Industrie 4.0!

Bei Fragen kommen Sie gerne auf uns zu (schinner@controlling.rwth-aachen.de).

Wichtiger Hinweis!
Falls Sie weiterführende Informationen über die Studienergebnisse wünschen, tragen Sie im folgenden Feld Ihre E-Mail-Adresse ein. Wir übersenden Ihnen dann am Ende der Hauptstudie einen Abschlussbericht.

Zurück | Weiter

100%

Vielen Dank für Ihre Teilnahme an dieser Vorstudie!
Wir werden Ihre Daten anonym auswerten und diese für die Entwicklung einer Studie zum Thema Thema „Wert von Kompetenzen im Zeitalter von Industrie 4.0“ nutzen.

Wir bedanken uns für Ihre Unterstützung!

Mit freundlichen Grüßen

Prof. Dr. Robert Böhm (Lehrstuhl für Decision Analysis),
Prof. Dr. Peter Letmathe (Lehrstuhl für Controlling der RWTH Aachen University),
Matthias Schinner (Lehrstuhl für Controlling der RWTH Aachen University)

Appendix III–8: Expert Survey (Translated Version; in English)

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Dear Sir or Madam,

we are planning a scientific study on the topic "Value of competencies in the age of Industry 4.0". The aim of the study is to investigate which competencies will be needed by mechatronics engineers in the future in order to master the new technological challenges arising from networking, automation as well as the digitalization of production and the associated complexity of the working world.

For this purpose, we have selected you - as one of 7 experts from industry - for this preliminary study in order to make a pre-selection of competencies listed in the literature for the main study. For this purpose, we ask you to indicate the probable importance of the listed competencies for the occupational profile of mechatronics technician on a given scale. Your selection should lead to a selection of the 16 most important competencies for the future in the occupational profile of mechatronics technician.

We would be very grateful if you would take 10 minutes to complete the following questionnaire. As a thank you, we will be happy to send you the detailed results of the main study exclusively before publication. If you are interested, please enter your e-mail address at the end of the questionnaire.

Otherwise, participation in the survey is, of course, anonymous. You can stop answering the questionnaire at any time and continue at a later date.

If you have any questions, you can reach us at the contact details below.

We thank you in advance for your support!

Yours sincerely

Prof. Dr. Robert Böhm
Prof. Dr. Peter Letmathe
Dipl. Kfm. Matthias Schinner

Correspondence address: Lehrstuhl für Controlling, RWTH Aachen University – Matthias Schinner – schinner@controlling.rwth-aachen.de

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25%

The rating of the competencies is conducted with regard to the developments in the field of Industry 4.0 for the occupational profile mechatronics technicians. Enclosed you will find a brief description of the field of activity of mechatronics engineers:

Mechatronics technicians work in the assembly and maintenance of complex machines, plants and systems in plant and mechanical engineering or at the customers and operators of these mechatronic systems. Mechatronics technicians carry out their work independently at various locations, primarily on assembly sites, in workshops or in the service area, in accordance with the relevant regulations and safety standards based on specifications and instructions. They often work as part of a team. They coordinate their work with upstream and downstream departments.
Mechatronics technicians are qualified electricians within the meaning of accident prevention regulations.

Core Professional Areas:
- Electromechanics
- Electronics
- Electrical engineering
- Hardware installation
- Software installation
- Industrial electronics
- Information technology
- Computer technology
- Mechatronics
- Assembly

You will then be taken directly to a selection of various competencies frequently mentioned in the literature. Please rate them according to their anticipated importance for the occupational profile of mechatronics technician in order to master the new technological challenges arising from networking, automation as well as digitalization of production and the associated novel complexity of the working world that will evolve in the future.

Back Continue

38%

The workplace within production companies will change significantly over the next few years as a result of new technological trends. Therefore, please rate the probable importance of the following competencies for the performance of mechatronics engineers in order to master the new technological challenges in the context of the developments of Industry 4.0, such as networking, automation as well as digitalization of production and the associated new complexity of the working world.

Below is the name of the competency of interest to be rated, as well as a brief description.

Dependability
Job requires being reliable, responsible, and dependable, and fulfilling obligations.

How important is the competency dependability for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Initiative
Job requires a willingness to take on responsibilities and challenges.

How important is the competency initiative for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Innovation
Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems.

How important is the competency innovation for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Stress tolerance
Job requires accepting criticism and dealing calmly and effectively with high-stress situations.

How important is the competency stress tolerance for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Independence
Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done.

How important is the competency independence for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Adaptability/flexibility
Job requires being open to change (positive or negative) and to considerable variety in the workplace.

How important is the competency adaptability/flexibility for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Attention to detail
Job requires being careful about details and thorough in completing tasks.

How important is the competency attention to detail for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Cooperation
Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude.

How important is the competency cooperation for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Persistence
Job requires persistence in the face of obstacles.

How important is the competency persistence for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Self-control
Job requires maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations.

How important is the competence self-control for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Analytical thinking
Job requires analyzing information and using logic to address work-related issues and problems.

How important is the competency analytical thinking for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

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50%

The workplace within production companies will change significantly over the next few years as a result of new technological trends. Therefore, please rate the probable importance of the following competencies for the performance of mechatronics engineers in order to master the new technological challenges in the context of the developments of Industry 4.0, such as networking, automation as well as digitalization of production and the associated new complexity of the working world.

Below is the name of the competency of interest to be rated, as well as a brief description.

Information Ordering
The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).

How important is the competency structuring information for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Selective Attention
The ability to concentrate on a task over a period of time without being distracted.

How important is the competency selective attention for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Oral expression
The ability to communicate information and ideas in speaking so others will understand.

How important is the competency oral expression for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Inductive reasoning
The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).

How important is the inductive reasoning competency for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Mathematical Reasoning
The ability to choose the right mathematical methods or formulas to solve a problem.

How important is the competency mathematical reasoning for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Written expression
The ability to communicate information and ideas in writing so others will understand.

How important is the competence written expression for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Instructing
Teaching others how to do something.

How important is the competency instruction ability for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Oral comprehension
The ability to listen to and understand information and ideas presented through spoken words and sentences.

How important is the competency oral comprehension for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Written comprehension
The ability to read and understand information and ideas presented in writing.

How important is the competency written comprehension for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Problem sensitivity
The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem.

How important is the competency of problem sensitivity for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Deductive reasoning
The ability to apply general rules to specific problems to produce answers that make sense.

How important is the competency deductive reasoning for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

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63%

The workplace within production companies will change significantly over the next few years as a result of new technological trends. Therefore, please rate the probable importance of the following competencies for the performance of mechatronics engineers in order to master the new technological challenges in the context of the developments of Industry 4.0, such as networking, automation as well as digitalization of production and the associated new complexity of the working world.

Below is the name of the competency of interest to be rated, as well as a brief description.

Mathematics
Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.

How important are mathematics knowledge for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Customer & personal service
Knowledge of principles and processes for providing customer and personal services. This includes customer needs assessment, meeting quality standards for services, and evaluation of customer satisfaction.

How important is customer service knowledge for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Mechanical
Knowledge of machines and tools, including their designs, uses, repair, and maintenance.

How important is knowledge in the field of mechanical knowledge for the future performance of a mechatronics technician in the course of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

English language
Knowledge of the structure and content of the English language including the meaning and spelling of words, rules of composition, and grammar.

How important are knowledge of the English language for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Engineering and Technology
Knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services.

How important is knowledge in the field of engineering and technology for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Computers & electronics
Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.

How important is knowledge in the field of computers & electronics for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Production and Processing
Knowledge of raw materials, production processes, quality control, costs, and other techniques for maximizing the effective manufacture and distribution of goods.

How important is knowledge in the area of production & processing for the future perfomance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Design
Knowledge of design techniques, tools, and principles involved in production of precision technical plans, blueprints, drawings, and models.

How important is knowledge in the field of design for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Education & training
Knowledge of principles and methods for curriculum and training design, teaching and instruction for individuals and groups, and the measurement of training effects.

How important is knowledge in the field of education & training for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Electronics
Electrotechnical knowledge of machines and tools, including their designs, uses, repair, and maintenance.

How important is knowledge in the field of electrotechnical engineering for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

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75%

The workplace within production companies will change significantly over the next few years as a result of new technological trends. Therefore, please rate the probable importance of the following competencies for the performance of mechatronics engineers in order to master the new technological challenges in the context of the developments of Industry 4.0, such as networking, automation as well as digitalization of production and the associated new complexity of the working world.

Below is the name of the competency of interest to be rated, as well as a brief description.

Systems Analysis
Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.

How important is the competency of system analysis and understanding for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Critical thinking
Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.

How important is the competency critical thinking for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Complex problem solving
Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.

How important is the competency complex problem-solving for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Operations Monitoring
Watching gauges, dials, or other indicators to make sure a machine is working properly.

How important is the competency operations monitoring for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Programming
Writing computer programs for various purposes.

How important is the competency of programming for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Social perceptiveness
Being aware of others' reactions and understanding why they react as they do.

How important is the competency social perceptiveness for the future performance of a mechatronics technician in the course of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Technology Design
Generating or adapting equipment and technology to serve user needs.

How important is the competency of technology design for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Troubleshooting
Determining causes of operating errors and deciding what to do about it.

How important is the competency of troubleshooting for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Active Learning
Understanding the implications of new information for both current and future problem-solving and decision-making.

How important is the competency active learning for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Judgment & decision making
Considering the relative costs and benefits of potential actions to choose the most appropriate one.

How important is the competence Judgment & Decision Making for the future performance of a mechatronics technician in the course of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Time management
Managing one's own time and the time of others.

How important is the competency of time management for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

Learning Strategies
Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.

How important is the competency learning strategies for the future performance of a mechatronics technician in the context of Industry 4.0?

○ Not Important ○ Slightly Important ○ Neutral ○ Important ○ Very Important

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88%

Thank you for participating in our preliminary study on the topic of the value of competencies in the age of Industry 4.0!

If you have any questions, please feel free to contact us (schinner@controlling.rwth-aachen.de).

Important note!
If you would like to receive further information about the study results, please enter your email address in the following field. We will then send you a final report after the end of the main study.

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100%

Thank you for your participation in this preliminary study!
We will evaluate your data anonymously and use it to develop a study on the topic of "Value of Competencies in the Age of Industry 4.0".

We thank you for your support!

Yours sincerely

Prof. Dr. Robert Böhm (Chair of Decision Analysis, RWTH Aachen University),
Prof. Dr. Peter Letmathe (Chair of Management Accounting, RWTH Aachen University),
Matthias Schinner (Chair of Management Accounting, Aachen University)

IV Research Paper 3: Consequences of the Interplay between Volatility and Capacity for Workforce Planning and Employee Learning

Peter Letmathe
RWTH Aachen University

Matthias Schinner
RWTH Aachen University

Abstract: Organisations face increasing turbulences in their business environments through demand fluctuations. These fluctuations are driven by specific customer requirements, shorter lifecycles, and technology changes. More changes to processes and products are related to a higher frequency of production ramp-ups. To manage production ramp-ups successfully, employee learning is of central importance to reduce uncertainty and instability. Multiple research studies have shown that learning and training of shop-floor employees can significantly reduce production costs and improve product quality. However, training measures are often in conflict with employee capacity restrictions. We present an MIP workforce scheduling model that allows us to investigate the impact of demand volatility on learning-by-doing, forgetting, and training of employees in production ramp-up scenarios. We specifically focus on the interaction of demand volatility and employee capacity, and we analyse the consequences for the learning and training behaviour of employees. To obtain insights into cost-optimal learning patterns, we examine an extensive dataset that is based on 300 scenarios with varying demand volatility scenarios and capacity restrictions. Each scenario is calculated for 18 periods. Overall, we show how to generate learning and training strategies under different demand volatility and employee capacity scenarios, and we analyse the specific properties of our solutions.

1 Introduction

Organisations have to deal with increasing turbulences, for instance, through increases in volatility, ambiguity or complexity (Bennett and Lemoine 2014a, 2014b). The mentioned turbulences lead to a range of problems for companies, such as decreased service levels, increased stockouts as well as shortage costs (Kulp et. al 2004). Demand volatility is one of the most relevant cost drivers for companies, because they have to build safety stock and provide more resources in order to hedge against demand fluctuations and fulfil the demand of their customers at any time (Christopher and Holweg, 2011). Furthermore, shorter product lifecycles and increasing product diversification force companies to build capabilities in order to stay competitive and react flexibly to market requirements (Sayın and Karabatı 2006, Scholz-Reiter et al. 2007). These developments especially affect companies in the phase of production ramp-up, when the production output, the level of capacity utilisation and the skill levels of employees are low (Terwiesch and Bohn 2001, Surbier et al. 2014). Consequently, companies face challenging production ramp-ups, which are defined as the *'period between completion of development and full capacity utilization'* (Terwiesch and Bohn 2001, p. 1). The ramp-up phase is critical for the success of a product (Surbier et al., 2014) and in this phase it is important to quickly master problems, such as downtimes originating from machine breakdowns, or slow setups. For the success of ramp-ups, workforce learning is of central importance in order to reduce uncertainty and instability (Terwiesch and Bohn, 2001). Production ramp-ups are also a '*key learning opportunity'* (Lenfle and Midler 2009, p. 157) for reaching full utilisation of a company's production capacity.

Research studies have shown that learning and training of shop-floor employees can significantly reduce production costs and improve the quality of products. However, capacity restrictions are often in conflict with training measures (Anderson 2001) and limit the flexibility to react to fluctuations in demand (Zhang et al. 2012). Experienced employees with higher skill levels increase a company's flexibility and overall capacity (Terwiesch and Bohn 2001, Hansen and Grunow 2015). Yet little work has been done to analyse the effects of demand volatility and employee capacity restrictions as well as the interplay between both factors on learning, forgetting, training, achieved skill levels and efficiency gains of the employees during productions ramp-up. Thus, in this paper we examine the following research question: What is the impact of demand volatility and its interplay with employee capacity on the learning and training of employees in production ramp-up? To answer the research question, we analyse the effect of assigning learning-oriented tasks to employees. We present a Mixed-Integer

Programming (MIP) workforce scheduling model that considers learning-by-doing, forgetting and training of employees. We analyse the consequences of demand volatility in different employee capacity scenarios on learning-by-doing, forgetting and training behaviours, and on achieved skills of the employees as well as on efficiency gains through learning in a ramp-up environment.

The remainder of this paper is organised as follows: Section 2 develops the theoretical foundation of our workforce scheduling model. In section 3, we define our research hypotheses. In section 4, the basic model, the numerical example of our experimental design, and the analytical approach are introduced. The research outcomes are presented in section 5, and implications of our findings are discussed in section 6. Section 7 summarises our main results and discusses limitations and future research opportunities.

2 Literature Review

2.1 Learning, Forgetting and Training

Research on learning curves has increased massively since Wright (1936) described the learning curve effect which shows that labour costs per unit decrease with accumulated output of a worker (e.g., Argote and Epple 1990, Anzanello and Fogliatto 2011, Argote 2013). Due to learning effects, employees produce faster, at lower cost and with a higher quality when as they gain more experience with a task at hand (Biskup 2008, Argote 2013). Furthermore, the literature distinguishes between so-called autonomous learning and induced learning. Autonomous learning, which is also called learning-by-doing, results from repeating comparable tasks. Induced learning describes the possibility to enforce the learning process with targeted training activities (Adler and Clark 1991, Biskup and Simons 2004, Biskup 2008). Training is one possibility to realise faster efficiency gains, but it is expensive and employees cannot produce goods to satisfy customer demand while they are in training sessions (Biskup 2008, De Bruecker et al. 2015). Nevertheless, training could be particularly helpful for gaining specific skills or for avoiding negative effects, such as forgetting (Jaber et al. 2003). Moreover, employees can use their capacities for training in periods of low demand to prepare for periods of high demand (Valeva et al. 2017). Forgetting effects result in higher lead times per unit due to interruptions or quality problems when performing a task (Shafer et al. 2001). To accelerate learning and to avoid any negative consequences of forgetting, the literature has increasingly incorporated learning and forgetting effects into simulation and optimisation workforce models (Anzanello and Fogliatto 2011, De Bruecker et al. 2015). In this research, we define skills, as De Bruecker et al. (2015, p. 2) do, *'as the ability to perform certain tasks well.'*

In the field of workforce scheduling, several models incorporate skills, learning, forgetting and training into production environments or as into production ramp-ups (Anzanello and Fogliatto 2011, Van den Bergh et al. 2013, De Bruecker et al. 2015, Afshar-Nadjafi 2021). Terwiesch and Bohn (2001) analysed autonomous learning and learning through experiments in a ramp-up environment. Sayın and Karabatı (2006) developed a two-stage optimisation model for assigning workers to tasks in the first stage and use a hyperbolic learning curve for optimizing skill development in the second stage. They show that the use of a skill improvement function leads to a more effective assignment of workers to departments (Sayın and Karabatı, 2006). Heimerl and Kolisch (2010) analysed the effect of company skill-level targets at the end of the planning period, which enlarge the skill-set of companies but also increase overall cost. Skill-level targets are also helpful for avoiding behaviours related to the end of the planning horizon in workforce scheduling models (Heimerl and Kolisch, 2010). Furthermore, a higher skill level at the end of the ramp-up fosters a higher capacity utilisation. Through the non-linear nature of learning curves, only small-size problems can be solved to optimality. To overcome this problem, it is common to use linearisations or approximations of learning and forgetting curves (Olivella et al. 2013, Hewitt et al. 2015, Valeva et al. 2017, Valeva et al. 2020).

2.2 Demand Volatility and Capacity Restrictions

Literature that considers learning, forgetting, and training often ignores the disturbances which can arise from factors like demand uncertainty and volatility (Valeva et al. 2017, Valeva et al. 2020). A high demand volatility can be found especially in highly competitive markets consisting of various and comparable providers of services or goods. There are three main possibilities for how demand can vary: A variation by trend, seasonal variations and stochastically selected variations (Zhang et al. 2012). The biggest challenge for companies occurs when demand volatility, defined as '*inconsistent, unstable, or high-variance demand for a company´s goods and services'* (Saldanha et al. 2013, p. 314), is not predictable or only predictable between defined boundaries. This results in additional costs due to overtime, unused capacity, excessive or insufficient inventory, materials handling or dissatisfied customers (Germain et al. 2008, Li and Hu 2017). In the same vein, the opportunity costs of volatility, such as shortage costs, should be taken into account (Inman and Gonsalvez, 1997). Often, companies react with higher stocks, overtime or outsourcing in order to buffer demand volatility (Zhang et al. 2009). According to Anderson (2001), demand volatility reduces the average productivity especially in cases of low employee turnover, low or negative company growth, or technology obsolescence rates. Additionally, capacity restrictions limit the flexibility to react to fluctuations in demand (Zhang et al. 2012). In consequence, demand volatility causes higher costs for companies and can potentially reduce their revenues.

Several models already incorporate stochastic demand volatility or employee capacity restrictions. Song and Hang (2008) see employee capacity as an important component within workforce planning, and they analysed the effects of different measures (transferring, hiring, firing) under random turnover and with uncertain demand requirements for the workforce. Mincsovics et al. (2008) analysed how to handle the relation between permanent and contingent capacity in order to meet stochastic volatile demand requirements. They showed that the optimal permanent capacity level should increase with higher demand volatility. Capacity in itself is often permanent, but capacity utilisation can be increased through learning and training and a higher level of experience of the employees, all leading to a higher productivity, i.e. a higher output per capacity unit (Terwiesch and Bohn 2001, Hansen and Grunow 2015). Especially when demand uncertainty is high, flexibility stemming from cross-training of skills can be more valuable than perfect information about demand (Campbell, 2011). However, most of the studies which incorporate demand volatility do not incorporate effects from employee skill development. Valeva et al. (2020) and Valeva et al. (2017) analysed the influence of demand variability on three levels (low, medium, high). To the best of our knowledge, they deliver the most comprehensive research work which takes employee learning and training also into account in order to manage demand volatility and uncertainty over several periods (Valeva et al. 2017, Valeva et al. 2020). Therefore, we analyse the impact of demand volatility and its interplay with employee capacity which can be influenced through the learning-by-doing, forgetting and training of employees in production ramp-up more systematically and in greater depth.

3 Research Hypothesis

In order to answer the research question, i.e. to examine the impact of demand volatility and its interplay with employee capacity on the learning and training of employees in production ramp-ups, we formulate three groups of hypotheses which will guide us in the following analyses. Afterwards, we propose a mathematical model which contains the relevant variables for testing the hypotheses with a large simulated dataset.

The first group of hypotheses explores the effect of demand volatility on learning-by-doing, forgetting and training. A consequence of demand volatility is a fluctuation between production activities, which results in unbalanced learning-by-doing and more forgetting. Some demands might not be fulfilled due to insufficient capacity and employees might also miss learning opportunities due to a lower production volume.

Consequently, we expect that learning-by-doing will be negatively affected by demand volatility. In addition, the assignment of employees to production tasks can be one-sided over several periods. In contrast to a balanced production program, this results in fewer opportunities for learning-by-doing during production activities, and the fact that employees are not assigned to certain activities for several periods leads to an increase in forgetting.

In periods with low demand, there is sufficient unused capacity available for training measures and employees can use it to prepare for periods with higher demand (Valeva et al. 2020) during which capacity is limited and employees have to avoid shortage costs. In addition, training measures can help to avoid forgetting (Glock et al. 2012) and thus to achieve a company's skill-level targets. For this reason, we expect the intensity of training to increase with a higher volatility of demand.

Hypothesis 1a: Learning-by-doing is negatively affected by demand volatility.
Hypothesis 1b: Forgetting is positively affected by demand volatility.
Hypothesis 1c: Learning through training is positively affected by demand volatility.

The second group of hypotheses is related to the achieved skills and the efficiency gains which will be obtained through learning-by-doing and training. Anderson (2001) stated that demand volatility has a negative impact on productivity. In contrast, higher skill levels should increase productivity and capacity utilisation and help to avoid negative effects from demand fluctuations (Heimerl and Kolisch 2010, Hansen and Grunow 2015). Achieved skills decrease through forgetting and having fewer opportunities for learning-by-doing and they increase with training intensity. If the effect from fewer opportunities for learning-by-doing and more forgetting is higher than from an increased training intensity, achieved skills will decrease. As we expect that in this case companies will prefer to avoid shortage costs rather than investing in training, the use of training measures is often limited due to employee capacity constraints (Anderson 2001). Hence, effects from an unbalanced production schedule (decreased learning-by-doing and increased forgetting) will overweigh the positive effects of (limited) training measures. Consequently, we hypothesize that achieved skills will be negatively affected by demand volatility. Since efficiency gains are closely related to the achieved skill levels and since increasing demand volatility, as mentioned above, affects skills levels negatively, we also expect negative effects from demand volatility on efficiency gains.

Hypothesis 2a: Achieved skills are negatively affected by demand volatility.
Hypothesis 2b: Efficiency gains are negatively affected by demand volatility.

The third group of hypotheses focusses on the interaction effects of demand volatility and employee capacity and how these interactions influence achieved skills and efficiency gains. We assume that increasing demand volatility has a negative impact on achieved skill levels and efficiency gains, but that the effect depends on the capacity level. Consequently, we expect an interaction effect between these two variables. Learning-by-doing depends on the amount of production activities, which is related to the employee capacity restrictions. With low employee capacity, it is more difficult to balance the fluctuations and to train the appropriate skills in order to avoid capacity shortages in periods of high demand. In consequence, achieving a higher level of skills should be less problematic with higher capacity levels, where times of low demand can be used for effective training. Hence, achieved skills as well as efficiency gains should increase with higher volatility and a higher capacity because employees are then less frequently interrupted disturbed by the turbulences of demand volatility and can use capacity buffers in periods of low demand to increase their skill levels and individual efficiency.

Hypothesis 3a: Achieved skills are positively affected by the interaction of demand volatility and capacity, i.e. high-capacity levels allow the use of capacity for employee training.
Hypothesis 3b: Efficiency gains are positively affected by the interaction of volatility and capacity.

4 Methodology

To test our hypotheses, we propose a task assignment model that allows for individual learning-by-doing, forgetting and training. This work aims to illustrate a multi-skilled workforce meeting stochastic demand volatility scenarios, while satisfying all constraints in different employee capacity scenarios. Furthermore, due to the linearisation of the learning curve into a step-wise function, the model can be calculated within a reasonable computing time. It should be noted that the presented model is not intended for practical scheduling applications.

4.1 Model Development

The following indices are used in the model:

l	Production activity (*l = 1,…,L*)
j	Product (*j = 1,…,J*)
t	Period (*t = 0,…,T*)
h	Employee (*h = 1,…,H*)
k	Skill level (*k = 1,…,K*)

The following parameters are included in the model:

c_{kl}	Costs for processing one production activity *l* with skill level *k*
b_{kl}	Required time for processing production activity *l* with skill level *k*
e_l	Costs to gain one skill unit through training of production activity *l*
tr_l	Required time per training to gain one skill unit for production activity *l*
a_{jl}	Output of product *j* from production activity *l*
D_{jt}	Demand for product *j* in period *t*
$\overline{Cap_h}$	Time-capacity of employee h for every period *t*
w_h	Individual forgetting of employee h in skill units
v_h	Individual learning-by-doing per production unit of employee h in skill units
f_l	Number of necessary repetitions of production activity *l* (or training) for employee h to avoid forgetting
z_{kl}^{min}	Minimum level of skill units for processing production activity *l* with skill level *k*
sc_j	Shortage costs of product *j*
M	Big M
ϕ_h	Company skill level target of employee h in period *t=T*

Variables:

r_{hklt}	0 if the skill level *k* of employee *h* could be used in period *t* for production activity *l*; 1 otherwise
fo_{hlt}	0 if forgetting does not occur because employee h is allocated more than f_l times to production activity *l* in period *t*; 1 otherwise
ys_{lt}	Amount of all production activity *l* in period *t*

y_{hklt}	Amount of all production activity *l* performed by employee *h* with skill level *k* in period *t*
yt_{hlt}	Amount of all production activity *l* performed by employee *h* in period *t*
u_{hlt}	Skill development through training of employee *h* for production activity *l* in period *t*
z_{hlt}	Skill units of employee *h* in period *t* for production activity *l*
sh_{jt}	Amount of shortage of product *j* in period *t*

$$\sum_{h=1}^{H}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{kl} * y_{hklt} + \sum_{h=1}^{H}\sum_{l=1}^{L}\sum_{t=1}^{T} e_l * u_{hlt} + \sum_{t=1}^{T}\sum_{j=1}^{J} sc_j * sh_{jt} \to min \qquad (1)$$

Constraints:

$$\sum_{l=1}^{L} a_{jl} * ys_{lt} = D_{jt} - sh_{jt} \qquad j=1,\dots,J;\ t=1,\dots,T \qquad (2)$$

$$yt_{hlt} = \sum_{k=1}^{K} y_{hklt} \qquad h=1,\dots,H;\ l=1,\dots,L;\ t=1,\dots,T \qquad (3)$$

$$ys_{lt} = \sum_{h=1}^{H}\sum_{k=1}^{K} y_{hklt} \qquad l=1,\dots,L;\ t=1,\dots,T \qquad (4)$$

$$\sum_{k=1}^{K}\sum_{l=1}^{L} b_{kl} * y_{hklt} + \sum_{l=1}^{L} tr_l * u_{hlt} \leq \overline{Cap}_h \qquad h=1,\dots,H;\ t=1,\dots,T \qquad (5)$$

$$z_{hlt} = z_{hl(t-1)} - w_h * fo_{hlt} + v_h * yt_{hlt} + u_{hlt} \qquad h=1,\dots,H;\ l=1,\dots,L;\ t=1,\dots T \qquad (6)$$

$$y_{hklt} \leq M * (1 - r_{hklt}) \qquad h=1,\dots,H;\ k=1,\dots,K;\ l=1,\dots,L;\ t=1,\dots,T \qquad (7)$$

$$z_{hlt} - z_{kl}^{min} \geq -M * r_{hklt} \qquad h=1,\dots,H;\ k=1,\dots,K;\ l=1,\dots,L;\ t=1,\dots,T \qquad (8)$$

$$\sum_{l=1}^{L} z_{hlt} \geq \phi_h \qquad h=1,\dots,H;\ t=T \qquad (9)$$

$$yt_{hlt} + u_{hlt} + M * fo_{hlt} \geq f_l \qquad h=1,\dots,H;\ l=1,\dots,L;\ t=1,\dots,T \qquad (10)$$

$$yt_{hlt} + u_{hlt} + M * fo_{hlt} < (M + f_l) \qquad h=1,\dots,H;\ l=1,\dots,L;\ t=1,\dots,T \qquad (11)$$

$$y_{hklt} \geq 0 \qquad h=1,\dots,H;\ k=1,\dots,K;\ l=1,\dots,L;\ t=1,\dots,T \qquad (12)$$

$$yt_{hlt} \geq 0 \qquad h=1,\dots,H;\ l=1,\dots,L;\ t=1,\dots,T \qquad (13)$$

$$ys_{lt} \geq 0 \qquad l=1,\ldots,l;\ t=1,\ldots,T \tag{14}$$

$$z_{hlt} \geq 0 \qquad h=1,\ldots,H;\ l=1,\ldots,L;\ t=1,\ldots,T \tag{15}$$

$$u_{hlt} \geq 0 \qquad h=1,\ldots,H;\ l=1,\ldots,L;\ t=1,\ldots,T \tag{16}$$

$$sh_{jt} \geq 0 \qquad j=1,\ldots,J;\ t=1,\ldots,T \tag{17}$$

$$\mathrm{r}_{hklt} \in \{0,1\} \qquad h=1,\ldots,H;\ k=1,\ldots,K;\ l=1,\ldots,L;\ t=1,\ldots,T \tag{18}$$

$$fo_{hlt} \in \{0,1\} \qquad h=1,\ldots,H;\ l=1,\ldots,L;\ t=1,\ldots,T \tag{19}$$

The objective function (1) minimises the production costs, training costs and costs for product shortages for the whole planning horizon. The approximation of the learning curve through the skill level k reflects the position of the steps on the learning curve and is characterized by the skill-level-dependent cost rate c_{kl} as well as the skill-level-dependent processing time b_{kl} for each production activity l. We assume that in every period t a given demand D_{jt} for each product j has to be produced. There are no safety stocks included, but a (costly) shortage sh_{jt} can be subtracted from the demand D_{jt} reflecting the unfulfilled demand (2). The amount of all production activities l processed by employee h in period t is denoted by yt_{hlt}. It summarises all different skill levels k of an employee h in period t (3). The sum of all different skill levels and all employees h for a certain production activity l in period t is denoted by ys_{lt} (4). Constraint (5) assures that the limited time capacity $\overline{Cap_h}$ of each employee h is satisfied. Constraint (6) defines the skill units of employee h regarding activity l in period t, denoted by z_{hlt}. The constraint incorporates learning-by-doing, forgetting, and training. Constraints (7) and (8) ensure that an activity is only feasible if the required minimum skill level is met or exceeded. In line with the argumentation above, a minimum skill level target ϕ_h for every employee h for the end of the planning horizon T is defined in constraint (9). The constraints (10) and (11) define a minimum amount of training or learning to avoid forgetting. The constraints (12) - (17) include the non-negativity integer constraints.

4.2 Numerical Example

We now present a numerical example that allows us to investigate the properties of our model in order to answer our research questions and to test our related hypotheses. To be best able to understand the influence of demand volatility in different employee capacity scenarios, we generated our own dataset that was not validated for a particular organisation or industry sector. Nevertheless, it reflects empirically validated patterns of learning-by-doing, forgetting and training. The defined input parameters are summarised in Table IV–1. The planning horizon is constant with T = 18 periods for the ramp-up phase. The example includes four employees H = 4 and J = 3 products. These products can be produced by employing L = 6 production activities. Allowing for substitution of activities each product can be produced with two exchangeable activities. In real shop-floor scenarios, process substitution is possible if a product can be produced on different machines at different cost rates (Hartl and Kort 1997, Letmathe and Wagner 2018). In order to better illustrate the properties of the model, the three products distinguish each other in terms of their cost levels: product 1 is produced at a relative low-cost level compared to product 2 (medium cost level) and product 3 (high cost level). Each production activity has a different cost rate c_{kl} related to the defined discrete skill levels K = 4, with cost for a given activity l decreasing when the relevant skill level increases. The respective four steps of the learning curve are expressed through z_{kl}^{min} and the costs depend on the achieved skills units z_{hlt} of the respective employee (see all cost structures in Appendix IV–1). In addition, the required time-capacity for processing a production activity b_{kl} depends on the achieved skill units of the employees as well. With a higher skill level, the time-related efficiency gains increase (see the decrease of b_{kl} with a higher skill level in Appendix IV–2). These (linearised) features of the model reflect empirical and theoretical findings related to the learning curve concept as discussed in section 2. All employees start with an initial skill level of z_{hl0} = 30. Further parameters, i.e. learning-by-doing v_h = 1, forgetting w_h = 10, required time capacity for training tr_l = 2, and training costs e_l = 5 remain constant during the entire planning horizon. To analyse differences of shortage costs, we assume the shortage costs sc_j for product 2 to be higher than for the other two products (see all constant parameters in Appendix IV–3). We define M with 100000. At the end of the ramp-up in period 18 we require a minimum skill level target ϕ_h= 750 which every employee has to reach.

Table IV–1: Test Instance Values

Factors	
Constant Factors	**Notation and Settings**
• Employees	$h \in \{1,2,\ldots,4\}$
• Number of products	$j \in \{1,2,\ldots,3\}$
• Number of production activities	$l \in \{1,2,...,6\}$
• Planning horizon	$t \in \{0,1,...,18\}$
• Skill-level 1,2,3,4	1: [1,50) 2: [50,200) 3: [200,500) 4: [500, ∞)
Variable Factors	
• Demand volatility	$\Omega \in \{1,2,...,100\}$
• Employee capacity	$\overline{Cap_h} \in \{200,375,550\}$

Overall, we ran the described model with 300 scenarios accounting for 100 different levels of demand volatility and 3 different capacity level. Each scenario covered a planning horizon of 18 periods. Demand volatility started with a value of one (one maximum variation compared to average product demand) and was increased by one percent all the way up to one hundred percent. Hence, one hundred different levels of demand volatility were simulated. To create different capacity environments for each level of demand volatility, the scenarios were simulated for three employee capacity scenarios: low (200 time-units per employee), medium (375 time-units per employee) and high (550 time-units per employee). Within the low-capacity scenario, the employees were not able to fulfil the average demand. Capacity in the medium-capacity scenario, was sufficient to fulfil the average demand (no volatility) with the employees' initial skill levels. In the high-capacity scenario, employees had enough capacity for production as well as training. We have no stock in our model. Consequently, an increase of demand volatility should lead to shortages because of insufficient capacity for the respective period in the low- and medium-capacity scenarios.

For modelling the presented Mixed-Integer Programme (MIP), we used the GAMS (General Algebraic Modeling System) software package. MIPs are frequently employed for staff scheduling models with different skills (Afshar-Nadjafi, 2021). For the solution of the described model, we used the Gurobi 7.5.2 Solver because it is appropriate for solving MIPs in an acceptable time. We terminate the runs after a relative gap of 4 % or a limit of five hours run time has been reached in order to obtain near-optimal solutions. The gaps differ between an average of 6.59 % for the medium-capacity scenario, 4.52 % for the high-capacity scenario and 3.98 % for the low-capacity scenario. Within the different capacity scenarios, we do not find significant differences for the gaps when accounting for different levels of demand volatility. Cost distribution and learning behaviour appear to be unaffected by the gaps.

4.3 Analysis Methodology

To examine the hypotheses and to identify the most significant variables, we employed Generalised Estimating Equations (GEE) using the open-source platform R (version 3.6.1). The GEEs were performed using the geepack package (Halekoh et al., 2006). GEEs are an extension of generalized linear models (Liang and Zeger, 1986) and one of the most effective statistical methods for analysing longitudinal data (Horton and Lipsitz, 1999). One major advantage of GEE is its robustness even when key assumptions are not fulfilled (Liang and Zeger, 1986). We chose a Gaussian distribution and the identity link option in order to correspond to a linear model (Ballinger, 2004). For the correlation matrix, we used an AR(1) structure because this structure is appropriate for time-dependent correlation structures in longitudinal studies (Ballinger, 2004). As dependent variables we use five variables with regard to our formulated hypotheses. We analyse the learning-by-doing with LJ_t, forgetting with FOR_t and training with P_t. Furthermore, as the aim of the ramp-up phase is that the employees reach a higher skill level, we measure the continuous variable 'achieved skill units' ACS_t which reflects the sum of the skill units (z_{hlt}) of all employees in the respective period and which is a composite measure of learning-by-doing, forgetting and training. A higher amount of skill units results in higher efficiency gains and is defined by EG_t (see for an overview of all dependent variables). The variables ACS_t and $EG_{t.}$ reflect also the aim of the ramp-up phase to acquire necessary skills and to improve the utilisation of the available capacity.

Table IV–2: Dependent Variables[1]

Dependent variable	Notation	Description
Learning-by-doing	LD_t	The sum of all learning-by-doing over all employees per period
Forgetting	FOR_t	The sum of forgetting over all employees per period
Training	P_t	The sum of all learning through training over all employees per period
Achieved skill units	ACS_t	The sum of all achieved skill units over all employees per period
Efficiency gains	EG_t	The sum of all efficiency gains through learning over all employees per period

[1] The mathematical definitions for the dependent variables can be seen in Appendix IV–4.

For every dependent variable, we test our hypotheses with six models (a-f). In model (a), the main explanatory variables are 'demand volatility' and 'employee capacity.' As a control, we also accounted for period effects, which are also our panel variable. The descriptive analysis indicates a nonlinear effect of employee capacity on the dependent variables. To address this within a GEE analysis, a quadratic (squared) term can be added to the existing models (Twisk, 2013), which is included as a quadratic term for employee capacity (capacity^2) in model (b)-(c). In model (c) we include an interaction term for demand volatility and employee capacity (volatility*capacity) which allows us to test the hypotheses (3a) and (3b). Additionally, we analyse the different employee capacity scenarios in model (d)-(f) with demand volatility and time as independent variables.

5 Results and Analysis

5.1 Descriptive Statistics

The following analyses are based on the 300 scenarios described above, each covering 18 periods. Before we test the formulated hypotheses, we first present the most important descriptive results. Figure IV–1 shows the average cost for the training, production and product shortage per scenario. The differences between the low-capacity scenario and the other scenarios are mainly driven by the shortage cost. Consequently, the production cost is lower in the low-capacity scenario than it is in the other scenarios. Surprisingly, the cost levels for training are higher in the medium-capacity scenario than in the high-capacity scenario. Figure IV–2 shows the average cost development through the whole ramp-up phase. Interestingly, in the medium-capacity scenario, the average cost per period is at the same level after nine periods as in the high-capacity scenario. Furthermore, we can observe that the average cost increases with an increasing demand volatility (see Figure IV–3). Additionally, Figure IV–4 shows that not only the training intensity (P_t) but also the timing for training differs between the three scenarios. In the low-capacity scenario, the training intensity is constant through all periods and in the high-capacity scenario, training is mainly performed in the first periods.

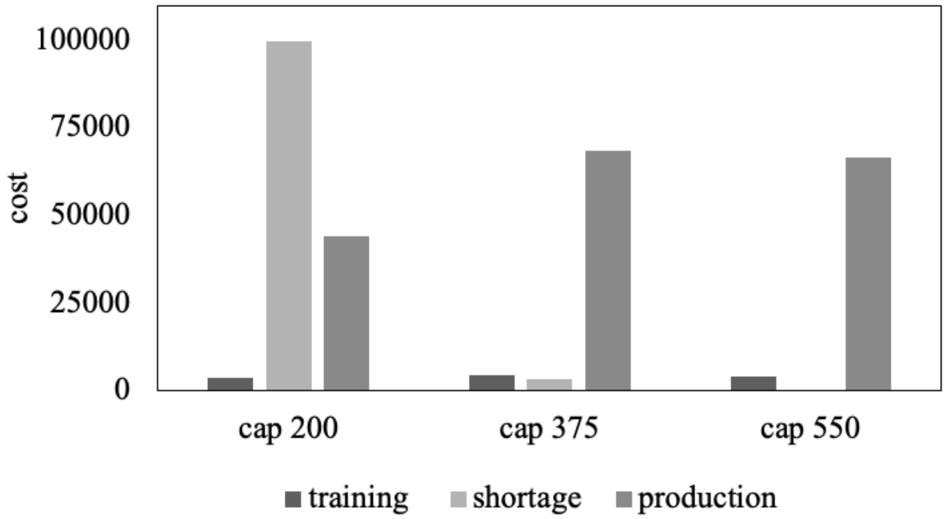

Figure IV–1: Average Cost per Period for Training, Production, and Shortage per Capacity Scenario

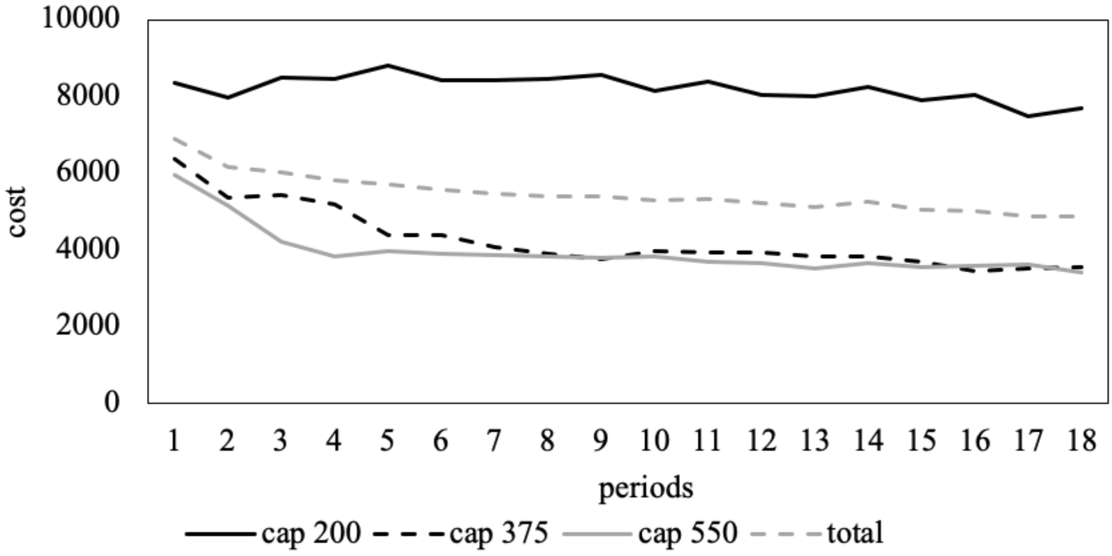

Figure IV–2: Average Cost Development over Planning Horizon per Capacity Scenario

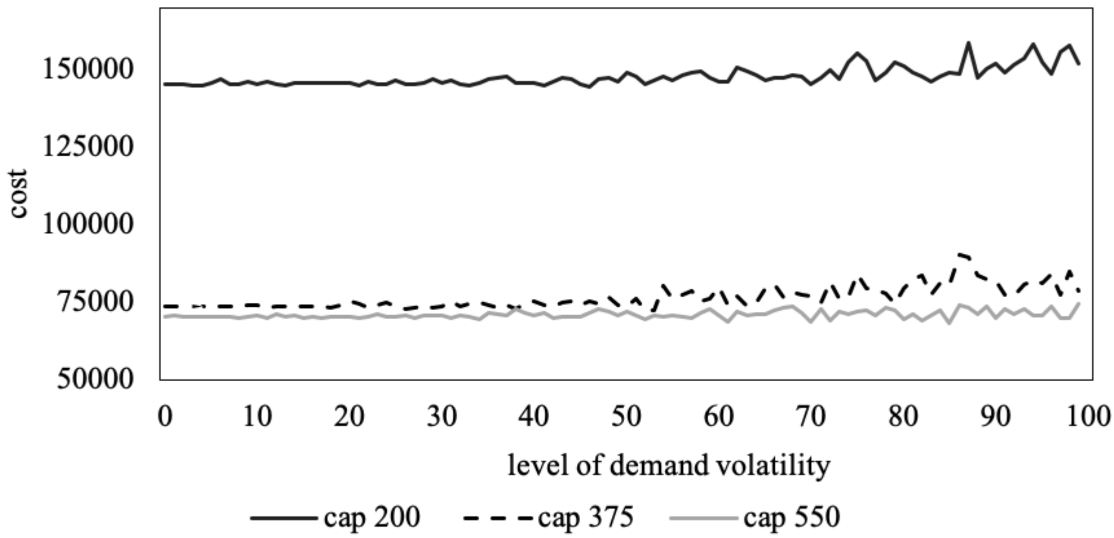

Figure IV–3: Total Cost Development through Volatility per Capacity Scenario

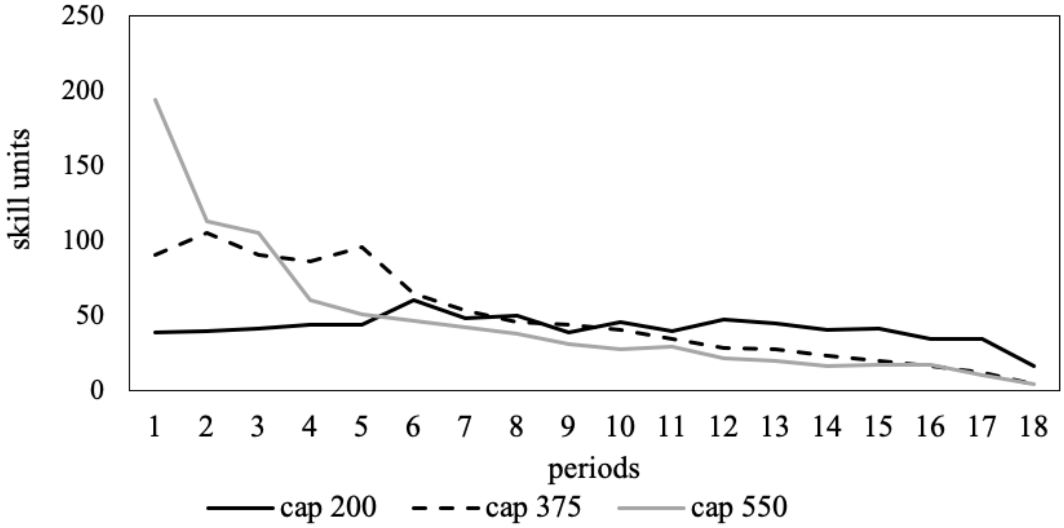

Figure IV–4: Training Development per Capacity Scenario

The results on the skill-level targets of 750 skill units for each employee at the end of the period generate interesting implications. Figure IV–5 shows the different values for the average achieved skill units of the four employees. While the minimum skill levels are only reached in the low-capacity scenario, they are clearly exceeded in the other two scenarios. This is an indicator that these skill level targets only represent a further restriction in the low-capacity scenario, whereas they have no restrictive effect in the other two scenarios. Moreover, it seems that the increase in employee capacity does not yield another major gain in ACS_t when comparing the medium and the high scenario. In contrast, there is a substantial increase between the low scenario and the medium scenario for each employee. The same effect is obvious for the influence on EG_t. Surprisingly, in the first seven periods, the EG_t of the medium scenario have a higher average value compared to the high-capacity scenario (see Figure IV–6).

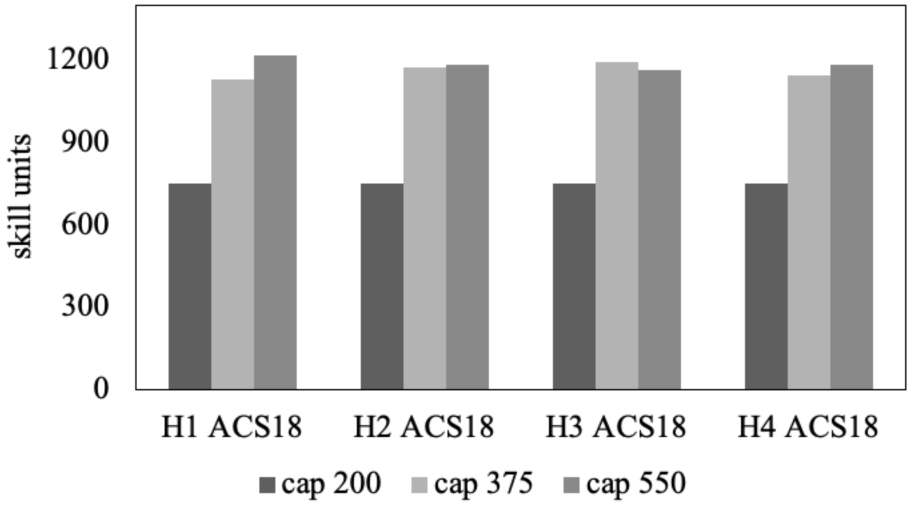

Figure IV–5: Average Skill Units (ACS) of the Employees (H) at the End of the Ramp-Up after 18 Periods per Capacity Scenario

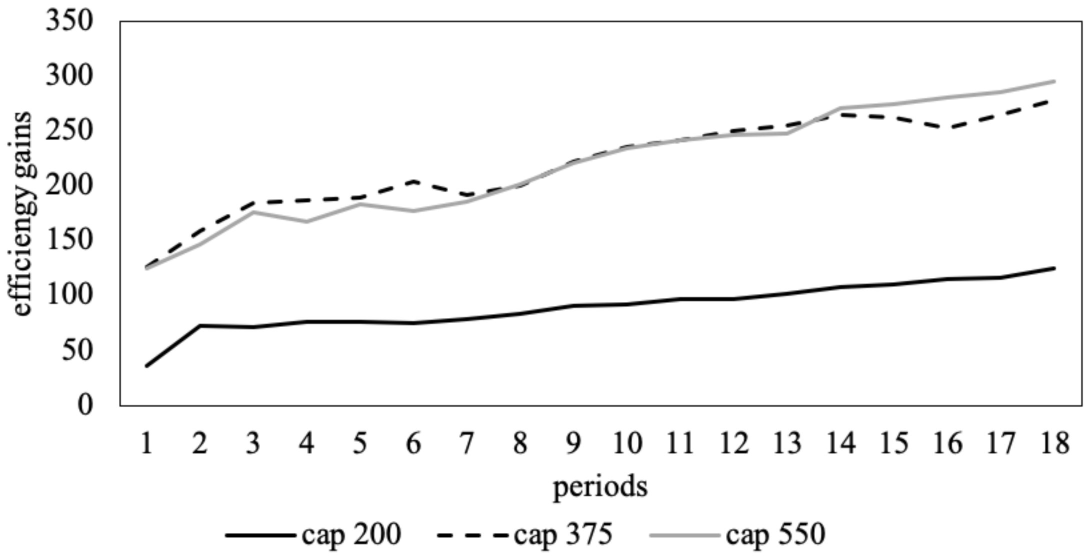

Figure IV–6: Development of Efficiency Gains during Ramp-Up per Capacity Scenario

5.2 Multivariate Analysis

We first analyse the learning-by-doing LD_t, forgetting FOR_t and the training behaviour P_t of the employees and how they are is influenced by an increasing demand volatility in the different capacity scenarios. Afterwards, we examine the impact on the achieved skill units ACS_t and the efficiency gains EG_t. We analyse the main effects for all instances and capacity scenarios. Finally, the impact of interaction effects on the achieved skill units ACS_t. and the efficiency gains EG_t will be discussed. Tables IV 3 to 5 include the analysis and the different models (a)-(f) for LD_t, FOR_t, P_t, ACS_t *and* EG_t. The quadratic term capacity^2 is highly significant in all models. Therefore, the influence of capacity can be better described by a non-linear function than by a linear one (Twisk, 2013). For this reason, we discuss in the following only the results from models (b)-(f).

Table IV–3: GEE Analysis: Learning-By-Doing and Forgetting

Capacity		***Dependent Variable: Learning-by-doing (LD_t)***							***Dependent variable: Forgetting (FOR_t)***					
		All levels			**Low 200**	**Medium 375**	**High 550**		**All levels**			**Low 200**	**Medium 375**	**High 550**
		Model 1a	**Model 1b**	**Model 1c**	**Model 1d**	**Model 1e**	**Model 1f**		**Model 2a**	**Model 2b**	**Model 2c**	**Model 2d**	**Model 2e**	**Model 2f**
Obser-vations		*N = 5400*	*N = 5400*	*N = 5400*	*N = 1800*	*N = 1800*	*N = 1800*		*N = 5400*	*N = 5400*	*N = 5400*	*N = 1800*	*N = 1800*	*N = 1800*
Intercept		102.96	-150.24	-146.32	154.96	301.14	297.30		16.41	-91.10	-87.69	68.35	79.91	46.61
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	H1a	-0.08	-0.08	-0.16	-0.07	-0.17	-0.001	H1b	0.10	0.10	0.03	0.11	0.05	0.16
		(0.170)	(0.000)	(0.000)	(0.000)	(0.000)	(0.150)		(0.000)	(0.000)	(0.059)	(0.000)	(0.000)	(0.000)
Time		0.60	0.55	0.55	1.07	0.27	0.29		4.00	4.01	4.01	0.22	4.68	7.22
		(0.000)	(0.000)	(0.000)	(0.000)	(0.140)	(0.340)		(0.000)	(0.000)	(0.000)	(0.069)	(0.000)	(0.000)
Capacity		0.39	1.97	1.96					0.14	0.80	0.79			
		(0.000)	(0.000)	(0.000)					(0.000)	(0.000)	(0.000)			
Capacity^2			-0.002	-0.002						-0.001	-0.001			
			(0.000)	(0.000)						(0.000)	(0.000)			
Volatility * Capacity				0.0002							0.0002			
				(0.000)							(0.000)			

The first observation in each cell is the estimate from the GEE regression analysis and the second observation (in brackets) is the two-sided p-value.

Table IV–4: GEE Analysis for Training and Achieved Skill Units

Capacity		Dependent variable: Training (P_t)							Dependent variable: Achieved skill units (ACS_t)					
		All levels			Low 200	Medium 375	High 550		All levels			Low 200	Medium 375	High 550
		Model 3a	Model 3b	Model 3c	Model 3d	Model 3e	Model 3f		Model 4a	Model 4b	Model 4c	Model 4d	Model 4e	Model 4f
Observations		*N = 5400*	*N = 5400*	*N = 5400*	*N = 1800*	*N = 1800*	*N = 1800*		*N = 5400*	*N = 5400*	*N = 5400*	*N = 1800*	*N = 1800*	*N = 1800*
Intercept		76.06	57.74	58.62	40.21	100.69	109.85		-376.73	-2222.30	-2166.70	667.30	1005.90	1054.86
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	H1c	0.15	0.15	0.13	0.17	0.07	0.21	H2a	0.02	0.004	-1.10	0.28	-1.54	1.30
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.960)	(0.980)	(0.001)	(0.025)	(0.000)	(0.000)
Time		-4.65	-4.65	-4.65	-0.77	-5.84	-7.60		185.98	186.37	186.37	129.41	216.37	212.86
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capacity		0.02	0.13	0.13					3.38	14.89	14.74			
		(0.000)	(0.000)	(0.000)					(0.000)	(0.000)	(0.000)			
Capacity^2			-0.0002	-0.0002						-0.02	-0.02			
			(0.000)	(0.000)						(0.000)	(0.000)			
Volatility* Capacity				0.00005				H3a			0.003			
				(0.530)							(0.003)			

The first observation in each cell is the estimate from the GEE regression analysis and the second observation (in brackets) is the two-sided p-value.

Table IV–5: GEE Analysis for Efficiency Gains

Capacity		Dependent variable: Efficiency Gains (EGt) All levels			Low 200	Medium 375	High 550
		Model 5a	**Model 5b**	**Model 5c**	**Model 5d**	**Model 5e**	**Model 5f**
Observations		*N = 5400*	*N = 5400*	*N = 5400*	*N = 1800*	*N = 1800*	*N = 1800*
Intercept		-34.96 (0.000)	-285.28 (0.000)	-273.59 (0.000)	54.76 (0.000)	158.89 (0.000)	119.42 (0.000)
Volatility	H2b	0.01 (0.920)	-0.01 (0.730)	-0.24 (0.000)	-0.02 (0.010)	-0.20 (0.000)	0.20 (0.000)
Time		7.42 (0.000)	7.01 (0.000)	7.00 (0.000)	3.83 (0.000)	7.57 (0.000)	9.53 (0.000)
Capacity		0.37 (0.000)	1.97 (0.000)	1.94 (0.000)			
Capacity^2			-0.0021 (0.000)	-0.002 (0.000)			
Volatility* Capacity	H3b			0.0006 (0.000)			

The first observation in each cell is the estimate from the GEE regression analysis and the second observation (in brackets) is the two-sided p-value.

Hypothesis 1a states that learning-by-doing is negatively affected by demand volatility. At first, we find a significant negative effect from volatility ($p < 0.001$) in model 1b. Furthermore, an increasing employee capacity affects LD_t significantly positively ($p < 0.001$). The quadratic term (capacity^2) is negative and significant ($p < 0.001$), and it shows that with an increase of capacity the effect decreases.

When analysing the different scenarios in models 1d, 1e and 1f separately, the influence of employee capacity becomes more salient. In the low- and the medium-capacity scenario (models 1d and 1e), we find the predicted negative effect of volatility (both $p < 0.001$). The effect is negative but insignificant ($p = 0.150$) in the high-capacity scenario (model 1f). This finding indicates that the capacity-creating effect of learning-by-doing is particularly pronounced in scenarios where capacity is a scarce commodity. Not implausible, this effect seems to be stronger than pure cost savings. In summary, these findings support Hypothesis 1a, but the effect of demand volatility almost disappears when employees have enough capacity to react to demand fluctuations.

In line with Hypothesis 1b, which predicts that forgetting is positively affected by demand volatility, demand volatility has a significant positive impact on FOR_t in model 2b ($p < 0.001$). This effect occurs also in the low-, medium- and high-capacity scenarios (each $p < 0.001$; model 2d-f). Furthermore, we find a significant impact of capacity on forgetting ($p < 0.001$) in model 2b. The quadratic term (capacity^2) is negative and significant, and it confirms the non-linear influence of the variable capacity.

We also find support for Hypothesis 1c which implies that learning through training is positively affected by demand volatility. In model 3b, which covers all capacity scenarios, the significance level is $p < 0.001$. The effect of volatility is also significant for the low-, medium- and high-capacity scenarios in the models 3d-3f (each $p < 0.001$). We also find a significant positive impact of capacity on training behaviour ($p < 0.001$) in model 3b. The squared term capacity^2 is highly significant and negative, indicating again a non-linear relationship.

Next, we analyse our two outcome measures, namely the achieved skill units ACS_t and the efficiency gains EG_t. Hypothesis 2a predicts that achieved skills are negatively affected by demand volatility. We found a u-shaped relation between these two variables for ACS_t. In model 4b demand volatility has a marginally positive but non-significant ($p = 0.980$) effect on the achieved skill units. When turning to the different capacity scenarios, we find contradictory results. In the medium-capacity scenario, demand volatility (model 4e) has, as predicted, a strong, negatively significant effect on ACS_t ($p < 0.001$) but in the low-capacity scenario (model 4d) a positively significant effect ($p = 0.025$) and in the high-capacity scenario (model 4f) a positively significant effect on ACS_t ($p < 0.001$) is found. Thus, the impact of volatility on ACS_t depends on the capacity level, which is also confirmed by the capacity control variable and the squared term (capacity^2) in model 4b (both $p < 0.001$). These findings seem to be puzzling at first glance. However, when deliberating on the mediating effect of capacity, it seems reasonable that demand volatility has the most severe consequences in the medium-capacity scenario: When capacity is too low to fulfil demand, some volatility will not change this situation and shortages will continue to occur. When capacity is high, demand volatility can be buffered to some extent. However, when capacity is just high enough to satisfy average demand, volatility hits hard, with the avoidance of shortages becoming the first priority and targeted learning the second.

Hypothesis 2b proposes that efficiency gains are negatively affected by demand volatility. For all capacity levels, we only find a marginally negative and insignificant effect ($p = 0.730$) from volatility on EG_t (model 5b). However, when analysing the different capacity scenarios separately, demand volatility has a significantly negative effect ($p < 0.010$) in the low-capacity scenario (model 5d) and in the medium-capacity scenario ($p < 0.001$; model 5e) and a strong and significantly positive effect ($p < 0.001$) for the high-capacity scenario in model 5f. In the low-capacity scenario, demand volatility has a significant negative influence ($p = 0.010$). Consequently, the variable capacity has a significant impact ($p < 0.001$). The quadratic term (capacity^2) is negative and significant ($p < 0.001$), and again shows the non-linear impact on EG_t (model 5b).

Again, these seemingly contradictory results may be attributed to the mediation effect of the employee capacity. Due to the capacity shortages in the low-capacity scenario, demand volatility does not seem to impact the efficiency gains significantly. When capacity is just sufficient as in the medium-capacity scenario, demand volatility disturbs the process of building up efficiency gains and therefore leads to a significantly negative effect (as predicted in Hypothesis 2b). Somewhat puzzling, when capacity is high, volatility can be buffered and volatility can even lead to higher efficiency gains. In summary, Hypothesis 2b is only partially supported.

After analysing the main effects, we find differences between the employee capacity scenarios. To obtain deeper insights, we analyse the interaction effects between demand volatility and employee capacity. Hypothesis 3a states, that achieved skills are positively affected by the interaction of demand volatility and capacity. In model 4c we found a significant and positive impact ($p = 0.003$) on ACS_t from the interaction of employee capacity and demand volatility and Hypothesis 3a is therefore supported. Hypothesis 3b predicts that efficiency gains are positively affected by the interaction of volatility and capacity, which is supported by our analysis ($p < 0.001$, see model 5c). The reported results show also time effects. P_t decrease significantly over time. All other dependent variables increase significantly with time. In the medium- and high-capacity scenarios only LD_t and in the low scenario FOR_t increase, but the time effect is insignificant.

6 Discussion

Our study has generated some key findings which we discuss now in more depth. First, we analysed the impact of demand volatility on learning-by-doing, forgetting and training. The negative impact of demand volatility on learning-by-doing is reasonably explained through the increase of shortages and the related decrease of learning-by-doing activities as well. This effect is particularly strong in the low-capacity and medium-capacity scenario. Obviously, it has a negligible impact in the high-capacity scenario because employees can balance out periods of high and low demand. Insufficient capacity in combination with an increasing volatility leads to higher shortage and a decrease of opportunities for learning-by-doing. For all capacity levels, an increase in demand volatility leads to an increase in forgetting and training activities.

However, when looking deeper into the underlying data, demand volatility leads to an unbalanced use of production activities resulting in unstable patterns of learning-by-doing and forgetting. By contrast, training opportunities help to avoid negative effects from demand volatility. In periods of low demand, workers can gain experience through training, which confirms results from the literature (e.g., Valeva et al. 2017). In this vein, companies use capacity in periods of low demand for preparing for periods with a higher demand. This explains further why the training intensity in the low-capacity scenario is nearly constant over the years (as there is no excess capacity) and the training in the high-capacity scenario is performed in the first periods. Consequently, when excess capacity is available in the early periods, training employees early during the production ramp-up generates higher benefits of learning.

Second, we investigated the impact of demand volatility on achieved skill units and efficiency gains. Overall, we found that these relationships are moderated by the available capacity. Specifically, the relationship between demand volatility and achieved skill units and efficiency gains are significantly negative in the medium-capacity scenario, significantly positive in the high-capacity scenario. Vice versa, in the low-capacity scenario, the effect is significantly positive for achieved skill units and significantly negative for efficiency gains. One explanation for these results is that in the medium-capacity scenario, demand volatility leads to more shortages and therefore learning-by-doing and training do not become the first priority. In the high-capacity scenario, it is easier to buffer shortages and to invest in training specifically in periods with low demand. In the low-capacity scenario, shortages occur anyway and investments in training only occur at a much lower level to achieve the target skill levels at the end of the planning horizon.

Third, we found effects from the interaction between demand volatility and employee capacity. In combination, both variables have a significant positive impact on the achieved skill units as well as on the efficiency gains.

The impact on efficiency gains is not surprising after having become aware of the moderating effect of capacity when analysing the different capacity scenarios separately. Hence, creating capacity buffers is one key to managing demand volatility. Additionally, we see how training measures can contribute to managing demand volatility in ramp-up phases of production. The three different capacity scenarios are strongly driven by different priorities. Overall, the results of the low-capacity scenario are driven by reaching the company skill-level target, the results of the medium scenario by avoiding shortage costs and the results of the high-capacity scenario by minimising production costs, as shortage costs are less relevant.

Our results show that it is of great importance for companies to take learning, forgetting, and training effects into account in their production planning in order to optimize their ramp-up processes. Depending on the capacity scenario, different priorities should be considered. These can be the skill levels of their employees, the avoidance of shortage costs and the reduction of production costs. Alternatively, it is of course possible to invest in higher capacity. However, such investments are often very costly and can exceed the cost of building up adequate skill levels during production ramp-up phases. As a result, managers should therefore adapt employee training programmes to the available capacity levels and set priorities accordingly.

7 Conclusions

The results of the computational study and analyses of the hypotheses provide insights that help to overcome the negative effects of increasing turbulences in business through demand volatility and how to manage workforce learning and training during production ramp-up phases. The proposed hypotheses were tested using an MIP which incorporates the mentioned factors and allowed us to simulate a rich data set. The results of the simulation scenarios were analysed with a GEE regression model, which is appropriate for longitudinal studies. The computational simulations demonstrate the value of modelling effects of learning-by-doing, forgetting, training, and the resulting efficiency gains. Even in this simple setting of three products and six productions processes over 18 periods, the assignment of workers to production activities is complex. In addition, most workforce planning systems do not enable managers to anticipate the consequences of their workforce planning decisions in this complex environment. We find interesting relations between demand volatility and employee capacity and have been able to demonstrate how beneficial it is to manage negative effects of demand volatility through learning and training during the ramp-up phase. As the computational study aimed at showing the distinct properties of the problems at hand, it is based on generated data and has therefore some limitations which can also point out directions for future research. As suggested in other studies, it would be reasonable for further research to test these kinds of models with real-world data in the future. For the practical application of the model, it would also be beneficial to develop heuristic approaches in order to reduce the computation times for more complex settings. Another promising avenue for future research would be to empirically investigate the effects of existing budgeting and allocation procedures for learning and training.

When considering our results, there seems to be substantial potential for better managing skill levels and turbulences such as demand volatility.

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Appendix

Appendix IV–1: Process Cost Structures c_{kl} for Different Skill Levels per Production Activity

	l = 1	l = 2	l = 3	l = 4	l = 5	l = 6
k = 1	10	8	20	19	40	40
k = 2	9	8	20	19	30	40
k = 3	8	8	18	19	20	40
k = 4	7	7	17	17	10	10

Appendix IV–2: Further Skill-Level-Dependent Parameters

	b_{kl}	ef_{kl}	z_{kl}^{min}
k = 1	5	0	1
k = 2	4,5	0,5	50
k = 3	4.2	0,8	200
k = 4	4	1	500

Appendix IV–3: Constant Parameters

w_h	v_h	e_l	tr_l	sc_{j1}	sc_{j2}	sc_{j3}	ϕ_h	f_l
10	1	5	2	40	70	40	750	10

Appendix IV–4: Mathematical Formulation of the Dependent Variables

Learning-by-doing	$LD_t = \sum_{h=1}^{H}\sum_{l=1}^{L} yt_{hlt} * v_h$	t=1,…,T;
Forgetting	$FOR_t = \sum_{h=1}^{H}\sum_{l=1}^{L} w_h * for1_{hlt}$	t=1,…,T;
Training	$P_t = \sum_{h=1}^{H}\sum_{l=1}^{L} u_{hlt}$	t=1,…,T;
Achieved skill units	$ACS_t = \sum_{h=1}^{H}\sum_{l=1}^{L}\sum_{t=1}^{t} z_{hlt}$	
Efficiency gains	$EG_t = \sum_{h=1}^{H}\sum_{k=1}^{K}\sum_{l=1}^{L} y_{hklt} * ef_{kl}$	t=1,…,T;

V Research Paper 4: Workforce planning in production with flexible or budgeted employee training and volatile demand

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Abstract: Companies have to adapt their product portfolio to rapidly changing markets and high demand volatility. As a result, they need to invest in workforce learning and training measures to gain flexibility. Especially during ramp-up phases employees have to adjust their skill set to new production requirements. While traditional employee training models focus on a condensed period of training at the beginning of a production ramp-up, we aim to shed light on the effectiveness of more flexible concepts of training with a general availability of training measures during a product's life cycle. We budget training in two dimensions, (1) training capacity per period and (2) periods that do not allow training. To analyze the impact of different training scenarios, a multi-period workforce scheduling problem with workers who learn through learning-by-doing and training is considered. The model further incorporates forgetting. We distinguish a flexible and a budgeted training environment. In the budgeted setting, training measures are only available in the first periods of a production ramp-up to a limited extent. Data from a computational study with 600 scenarios and near-optimal solutions are analyzed statistically to derive insights into an employee's skill development. Overall, we investigate different training strategies under demand volatility and capacity scenarios and analyze the specific outcomes in order to provide managerial implications. Our results indicate that traditional budgeting of training measures has a negative effect on employee learning. The negative impact of budgeting is stronger when production capacity is scarce and demand cannot be fully satisfied.

1 Introduction

Due to digitization and demographic changes, a variety of new challenges are arising for organizations (Surbier et al., 2014; Wisner, 1996). Costumers require updated products within shorter periods of time and, because of technological advances, production processes have often become more complex (Surbier et al., 2014). Since the 1990s, development times and product life cycles have been reduced substantially (Terwiesch and Bohn, 2001). The Companies often have to develop new products and bring them to market in less than a year, which equals the market time window for selling many products. A famous example is the cell phone industry where new models are introduced every year. To address rapid changes in customer preferences and technology, companies have to be able to adapt to new market requirements if they are to keep up with the constant rate of change (Qin et al., 2015). Hence, to meet the challenges of fast-changing markets with high demand volatility, companies have to adjust not only their product portfolio and services, they also have to invest in the fast ramp-up of new production processes (Hansen and Grunow, 2015). As these production processes are becoming increasingly interconnected, required employee skills are changing and existing skills might decrease in value over time (Letmathe and Schinner, 2017). Thus, project portfolio decisions should be based on the employees' competencies and take their targeted development into consideration (Gutjahr et al. 2010). If the returns of different products are known up-front or assessable during production, it is worthwhile for companies to focus on a specialized workforce when selecting a project (Gutjahr, 2011). However, especially during a product's ramp-up phase, which involves low production capacity and high demand, employees have to adjust their skill set to new requirements. Therefore, it is crucial for firms to invest in workforce learning and training measures (Terwiesch and Bohn, 2001). Hence, employee skill development and competence management alongside concepts of learning and forgetting as well as different concepts of training should become an integral part of workforce management practices. Traditional employee training models focus on a condensed period of training at the beginning of employment or during the implementation of a new production process (Ally, 2009). Such approaches limit training measures often by determining the available training budget and capacity and do not allow for training during the whole life cycle of a product. In this sense, companies have often a fixed budget of training measures that they can distribute among the work force. We aim to shed light on the effects of more flexible concepts of training which incorporate a general availability of training measures at all times. In order to compare traditional concepts of employee development with more flexible ones, we limit training measures in two dimensions. The training budget is defined by the available training capacity per period and periods which allow for training compared to those that prohibit training. Considering traditional, budgeted training, companies cannot react sufficiently flexibly to any demand oscillations. Thus, they are not able to use times of low demand for training in order to increase their skill levels. Moreover, high demand reduces the amount of time that can be used for training; thus, training opportunities are forgone. Since budgeting often only allows for training measures in the first periods, employees cannot recover the missed training opportunities in later periods. As a consequence of production ramp-ups incorporating high and unknown demand (Terwiesch and Bohn, 2001), the effect of budgeting training measures might increase with rising demand volatility and lower employee capacities. Consequently, the question arises: What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems? To analyze the impact of different training scenarios, a multi-period workforce scheduling model is considered with workers who gain experience by learning-by-doing and due to training or lose skill units through forgetting. Data from a computational study with near-optimal solutions obtained via GAMS and a Gurobi 7.5.2 solver are analyzed with General Estimation Equations (GEE) to derive insights on the production system's overall performance and skill outcomes depending on different training environments and demand volatility.

The remainder of the paper is structured as follows: section 2 provides the theoretical background on production ramp-ups, learning theory, and types of training. In section 3, we derive hypotheses for the main relationships of training and production outcomes with specific regard to employee training. We test these hypotheses with a set of simulated data generated through a mixed-integer optimization model that is presented in section 4. The last sections 5 and 6 present the results of our analysis and discuss our findings.

2 Theoretical Foundation

The implementation of new production processes, which can take up to a quarter of a product's life cycle, is known as the ramp-up phase and defined as the period '*between completion of development and full capacity utilization*' by Terwiesch and Bohn (2001, p. 1). They described three different kinds of ramp-up scenarios: plant ramp-up, product ramp-up, and process ramp-up (Terwiesch and Bohn, 2001). These are influenced by the same characteristics: uncertainty, high complexity (Surbier et al., 2014), interruptions, defects (Glock and Grosse, 2015), low production capacity, and high demand volatility (Terwiesch and Bohn, 2001). Hence the ramp-up phase is characterized by a trade-off between normal production and learning, which increases yields and decreases production times, which, vice versa, stimulates production output (Schultz et al., 2003). Since high demand oscillations are one of the main dynamic cost drivers, organizations have to build up safety stocks to cope with volatile demand patterns (Holweg et al., 2011). During ramp-ups, building these safety stocks is often impossible, as the productivity of the newly introduced production processes is low, and full capacity utilization is not possible in this phase (Schultz et al., 2003). However, the ramp-up phase is often also characterized by high demand for new products with customers willing to pay premium prices (Terwiesch and Bohn, 2001). Research on demand volatility has especially been carried out in the field of forecasting to enable more precise predictions (e.g., Abolghasemi et al. 2020). Although demand volatility is of great importance for production scheduling and workforce planning, forecasting models require historical data on which to base calculations. Such data are often absent in production ramp-up situations (Huang et al., 2008). Since the combination of demand volatility and unstable production processes is challenging to control in ramp-up scenarios, companies need to invest in the factor 'human resource' in order to increase production output and workforce flexibility and thus be able to meet the customer demand and achieve long-term stability (Qin and Nembhard, 2010). In this regard the production or project duration benefits from an even allocation of flexibility measures among available resources, i.e., workers or machines (Vairaktarakis, 2003). However, employees' time capacities are limited and cannot be extended flexibly to meet a given demand, thus these capacities limit production output per period. Hence, a trade-off between more efficient production by investing time into training and meeting customer wishes arises, especially when high demand volatility is present (Anderson 2001). Compared to capacity limits, capacity utilization can be increased due to learning and training when employees become more productive over time (Qin and Nembhard, 2010; Terwiesch and Bohn, 2001). High learning rates of workers in manufacturing production can lead to an increase in production quality as well as to a reduction in production costs and processing times (Yelle 1979; Dutton and Thomas 1984; Biskup 2008; Anzanello and Fogliatto 2011). These in turn enable workers to produce larger product quantities within the same time span (Argote et al., 2000). Therefore, in today's changing production environments, a redesign of workforce planning, scheduling, and training approaches is indispensable and can help companies to maintain their competitive advantages (Qin and Nembhard, 2015).

In 1936, Wright described the interdependency of the quantity produced and the time needed to execute a production task (Wright, 1936). By discovering that the amount of time workers needed to produce one unit decreases in a log-linear relation to the cumulative number of goods produced, he developed the first learning curve model with a constant learning rate. Since this discovery, extensive research has been carried out on different types of learning curves (Yelle 1979; Dutton and Thomas 1984; Jaber, Kher, and Davis 2003; Biskup 2008; Anzanello and Fogliatto 2011; Hansen and Grunow 2015). Anzanello and Fogliatto (2011) compared univariate learning curve models, e.g. log-linear, exponential and hyperbolic learning curves, with multivariate approaches. Globerson (1987), Globerson and Gold (1997) and Grosse, Glock, and Müller (2015) discovered that the log-linear model with a non-complex mathematical structure nevertheless estimates production based on manual tasks with sufficient precision. Consequently, the log-linear model is the most widely used learning curve in production-based scenarios (Dar-El et al., 1995; Yelle, 1979). In their review article, De Bruecker et al. (2015, p. 2) described the development of skills, as having a positive impact on an employee's '*ability to perform certain tasks well.*' They identified the following factors as being positively affected by employee skills: processing time, production efficiency, product quality, and labor costs. Not only does the performance with respect to a single task increase, experienced workers at high skill levels are further able to adapt to changes in the production process more efficiently (Wright, 1936).

In contrast to learning, forgetting has a negative influence on employee performance (Digiesi et al., 2009; Dode et al., 2016; Jaber et al., 2003). Thus, it decreases the skill levels of a worker and therefore production efficiency. Teyarachakul et al. (2011) provide an overview of ways in which forgetting has been modeled in manufacturing settings, e.g., depending on the number of interruptions, experience or skill level gained previously, or the duration of an interruption. Moreover, forgetting curves were found to be mirror images of learning curves and to be dependent on the respective production task (Globerson, Levin, and Shtub 1989). Jaber et al. (2003) presume that training measures cannot only foster learning but can also help to maintain achieved skill levels by counteracting any loss of skills by preventing forgetting.

In addition to learning-by-doing, skill enhancements and better capacity utilization can be generated by the training of employees (Carrillo and Gaimon, 2000). According to Chen et al. (2010), training decisions entail at which point in time (i.e., when) which skills or production tasks (i.e., what) should be trained by which worker (i.e., who). Thus, in the context of training decisions, workers are assigned to training sessions. In order to develop employee skills, training measures are typically affected by two dimensions of costs: direct costs for the training sessions and opportunity costs, as workers cannot use the training time for production (Büke et al., 2016). To reduce overall costs, achieve shorter lead times, create higher product quality, and increase workforce flexibility, employees can be cross-trained (Inman, Jordan, and Blumenfeld 2004; Yang and Kuo 2007). Cross-training enables workers to process different production activities which require distinct skills (Hopp and Oyen, 2004). Compared to purely relying on the specialization of employee skills, a broader set of skills allows companies to better cope with demand volatility, which influences the mix and quantities of tasks to be performed. Although the resulting high level of workforce flexibility enables a company to meet stochastic demand by re-assigning employees to a variety of tasks, further costs for cross-training may arise: e.g., additional training costs and wage payments, decreased efficiency and productivity of an employee, as well as transfer costs (Qin et al., 2015).

Traditional training approaches aim to build knowledge in a condensed learning period at the beginning of the employment or a new production process (Ally, 2009). Such budgeting approaches follow the rationale that learning should take place in the early phases of ramping up a new task and that follow-up learning does not need to be managed but happens somewhat automatically. In the same vein, sophisticated management of learning processes does not seem to be required, as initial learning takes place in the early phases of a ramp-up process and does not have to be planned in the later stages. However, in ramp-up scenarios, training and knowledge transfer can lead to a deceleration of the production process if not timed properly, as employees need to use their time for training instead of production (Szabó, 2018). Therefore, it is of special interest to investigate the influence of more flexible training concepts, allowing workers to time training suitably under consideration of different markets and demand or capacity environments. Hence, the traditional budgeting approaches should be refined and potentially extended to the entire planning horizon of a product's life cycle.

Valeva et al. (2017) analyzed the extent to which employee learning and forgetting can be used to cope with demand volatility. They took three different demand variation scenarios into account to model the influence on production and capacity utilization, but they did not distinguish between different approaches to employee training. Heimerl and Kolisch (2010) examined company skill targets at the end of the production phase to ensure sufficient skill development and to broaden a company's skill portfolio. Letmathe and Schinner (2021) analyzed how training measures can help to overcome the negative influence of demand volatility during production ramp-ups by showing that training measures can reduce the impact of demand volatility on skill development and productivity. These relationships are moderated by the available employee capacity. Their results show that if the time endowment of employees is sufficiently large, most of the training measures are used in the first periods of the ramp-up phase. In contrast to this, in scenarios with low employee time capacities, the number of training sessions undertaken appears to be rather constant in all periods.

Although the influence of novel training measures, which arise due to technological advances, has been investigated in the literature of Human Resource Development (Beardwell and Thompson, 2017; Chalofsky et al., 2014; Noe, 2010), to the best of our knowledge no such research has been carried out on the influence of the timing of training measures on workforce flexibility and workforce scheduling. We aim to contribute to the literature on workforce planning and ramp-up management by providing insights into the interaction between demand volatility and flexible training concepts compared to time-budgeted training. Furthermore, we focus on the interaction of training approaches and demand volatility in different employee capacity scenarios. We simulate demand volatility and different employee time capacity settings based on the approach of Letmathe and Schinner (2021). In contrast to the work of Letmathe and Schinner (2021), we include two scenarios to investigate the difference between flexible and traditional concepts of employee training. In the first setting, training measures are time-budgeted and training is only available in the first periods of production. This setting mirrors traditional concepts of employee skill development. In contrast, the second setting does not rely on a budgeted approach, i.e., employees can undergo training sessions in each period. Hence, workforce planning can react more flexibly to demand volatility.

3 Hypotheses

Considering the budgeted scenario, training measures are only available in the first periods of the planning horizon. Additionally, not only the periods which allow for training are limited but also the number of training sessions available per period. In consequence, we expect the number of training sessions undertaken by all employees in all periods to be significant lower if the access to training measures is budgeted, compared to the scenario with flexible training. This assumption aligns with the results of Letmathe and Schinner (2021), who found the number of training measures to be close to constant during all periods with scarce employee capacities. The results of (Valeva et al., 2020), who expect workers to train especially in periods of low demand, also support this finding. During the introduction phase of a new product, customers often pay premium prices with high demand. Thus, shortage costs are especially high during the ramp-up phase (Terwiesch and Bohn, 2001).

Such scenarios are especially relevant for industries with innovative products, e.g. electronics, where initial demand is often unpredictable when a new product is launched (Fisher, 1997). Henceforth, depending on the shortage costs, companies might forgo training opportunities rather than not meeting the given demand, even if employee training would not be available in later periods. Resulting from these expectations, the total learning output, which is the sum of learning-by-doing and learning through training, is expected to be significant lower in the budgeted training scenario. As it is not possible to use training measures to prevent forgetting in the periods following the initial ramp-up and as production as well as learning depend on volatile demand, we expect forgetting to be higher in the budgeted scenario compared to the more flexible non-budgeted setting. This expectation is in line with Jaber and Guiffrida (2008), who argued that training can prevent employees from forgetting and enables employees to maintain skill levels. Consequently, budgeting can lead to higher levels of forgetting and, thus skill units might decrease over time.

Throughout this paper, skill development is defined as the total learning output reduced by forgetting. Driven by the trade-off between learning-by-doing and training in the first periods of a production ramp-up and the lack of training measures to prevent forgetting and to foster employee skills in later periods, we assume the total skill development to be significant negatively impacted by budgeted training measures. Summarizing, we formulate the following hypothesis:

H1: The budgeting of training measures has a negative impact on skill development.

We model the amount of time needed to gain additional skills during a training session to be lower than gaining the same skill enhancement during production. Thus, a decision for learning-by-doing during production and against training sessions results in lower skill enhancement. Considering the trade-off between production and training measures, especially in the budgeted scenario, we expect the production quantity to decrease marginally because companies will use a minimum amount of time for training to profit from lower production costs and decreasing production time requirements in later periods.

Characteristic of scenarios with high demand volatility are oscillations between successive periods and uncertainty concerning the demanded amount (Huang et al., 2008). When companies have to face high volatility, they have to find a trade-off between meeting the given demand and investing in training opportunities in the respective periods. We expect companies to prefer to meet customer demand than to accept shortage costs. Thus, we predict a decrease in skill development regarding scenarios with high demand volatility. As training can also prevent forgetting, less training in high volatility scenarios might not only result in fewer newly adopted skill levels but might also lead to forgetting when workers are not assigned to a task for a longer period of time. Combining these factors, we derive the following hypothesis:

H2: Demand volatility has a negative impact on skill development.

Prior to the market introduction of a new product, not only is the actual demand per period unknown but also the general interest in the product itself. Therefore, companies may face different intensities of demand volatility. We model the impact of different levels of demand volatility relative to the workforce capacity. Hence, employees have a limited amount of time units per period, which can be used either for training or production. In each capacity scenario, all employees work the same number of hours per period, i.e., they have the same capacity in every period. In a low-capacity scenario, the initial time endowments of employees barely suffice to meet a given demand. Thus, the trade-off situation between production and training intensifies, as workers need to increase their skill levels to be able to meet the demand in the following periods. At the same time, scarce capacity makes it more difficult to buffer production against demand volatility, as there is no slack for additional production. Considering a medium-capacity scenario, workers can satisfy the demand using their initial skill endowment but do not have any time remaining for training or production if the demand substantially exceeds the average demand. Hence, demand volatility still plays a limiting role but to a lesser degree than in low-capacity scenarios. High-capacity scenarios enable workers to produce goods and undergo training measures simultaneously in most periods. Moreover, they enable employees to obtain higher skill levels due to training. This results in improvements in production time and costs. At the same time, it is possible to buffer production against demand volatility.

According to the settings described above, we aim to shed light on the effects of budgeted training measures in the different employee capacity scenarios. We expect the impact of budgeted training measures on the amount of training to be negative in the low and medium capacity scenarios but to vanish regarding the high-capacity scenario due to better buffering opportunities. Thereby, employees develop more skills through training in the first periods in the high-capacity scenario to prepare for any forgetting effects in later periods. Hence, we expect the interaction effect of employee capacity and budgeting on skill development to be positive regarding increasing capacity endowments. To put it another way: Traditional budgeting approaches are less detrimental if a production system has sufficient capacity buffers. The mentioned expectations result in the following hypothesis:

H3: Employees' skill development is affected positively by the interaction effect of budgeting and employee capacity.

Budgeting for training measures reduces the ability to respond to skewed or high demand when employees are not enabled to achieve higher skill levels through targeted on-the-job learning. In times of high demand volatility, periods with high demand that deviates from the average demand are typical. Considering that periods of high demand are also possible in the first periods of observation, we expect a decrease in undertaken training measures that is caused by shortage costs. This will, in turn, lead to fewer opportunities to increase production efficiency through training. In the later periods, there will be fewer opportunities for employees to undergo training sessions, even when demand is low and surplus time capacities are available. Consequently, efficiency gains that are necessary to meet the demand in periods with higher demand are forgone if budgeting and high demand volatility are present. Fewer opportunities for training in combination with unmet demand can therefore lead to a negative impact on employee skill development. Following this line of reasoning, we expect:

H4: Employees' skill development is affected negatively by the interaction effect of budgeting and demand volatility.

4 Methodology

To test the hypotheses concerning the influence of the budgeting of training measures and demand volatility, we use a mixed-integer optimization model based on Letmathe and Schinner (2021). This model contains the possibility of non-budgeted training and autonomous learning. Here, an extension of this model has been developed and then utilized to answer the formulated research questions. First, the model is introduced in section 4.1; second, in 4.2, the parameters used for the simulation are depicted.

4.1 Methodology

Let $i \in \{1,...,m\}$ denote the set of shop floor employees who can conduct a production activity $l \in \{1,...,L\}$ to produce products $j \in \{1,..,n\}$ in each period $t \in \{1,...,T\}$. Executing production activity l results in an output of l_j units of product j. Whereas each worker can theoretically perform each activity, each production activity allows the production of exactly one of the products relevant to meeting customer demand. Each employee i is characterized by a skill level for every production activity l in every period t, denoted by $z_{ilt} \geq 0$. Note, that this skill level can change over time due to training, learning-by-doing, or forgetting.

4.1.1 Skill Development

To obtain a linear program we use a linear approximation for our learning curve by introducing discrete skill levels $k \in \{1,\ldots,K\}$. Depending on the skill level k achieved due to skill units $z_{ilt} \geq 0$, the time required for processing production activity l, denoted by p_{kl} , and the production costs per unit, denoted by c_{kl}, differ. The required amount of skill units for processing production activity l at the skill level k is defined by $z_{kl}^{min} \geq 0$. In line with the learning curve theory, we assume production time and costs to decrease due to learning, i.e., with increasing skill levels. Forgetting and the two dimensions of learning are incorporated in the following ways:

First, we model learning-by-doing which occurs while executing production activity l in period t with skill level k, with $y_{iklt} \geq 0$ denoting the amount of product l produced in period t by employee i with skill level k. Employee i gains experience based on an individual linearized skill development or learning factor v_i . Second, we consider training measures with costs per training measure c_l and time units tr_l needed for one training unit. Both parameters depend on the production activity l. Further, $u_{ilt} \geq 0$ denotes the total amount of training measures for production activity l of employee i in period t. The training effects, i.e., the gains in skill levels, occur proportionally to the time spent on training for each activity. In each period, worker i is equipped with a constant time capacity $\overline{CAP_i}$ which can either be used for training or production, i.e.,

$\sum_{k=1}^{K}\sum_{l=1}^{L} p_{kl} * y_{iklt} + \sum_{l=1}^{L} tr_l * u_{ilt} \leq \overline{Cap_i}\ \forall i \in \{1,\ldots,m\}, t \in \{1,\ldots,T\}.$

As a counterpart to learning, we incorporate forgetting in our model. An employee i loses w_i skill units for a certain production activity l, according to his or her individual linearized forgetting factor, if she or he gains fewer then fl_l skill units for this production activity in the respective period. Thus, the amount of skill units forgotten depends on the length of the interruption, as it is possible that forgetting occurs in several successive periods, and on the experience gained so far due to the discrete skill level k. To display forgetting, we incorporate the binary variable fg_{ilt} with fg_{ilt} = 1 if employee i earns less than fl_l skill units due to training or processing of production activity l in period t, and fg_{ilt}= 0 if he does not lose skill units. Hence, we add the two constraints (1) and (2) to the model to determine if a worker i experiences forgetting effects for production activity l in period t measured by the binary variable fg_{ilt}. Therefore, we chose the big M constant $M > 0$ to be a sufficiently large number.

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} \geq fl_l \qquad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \tag{1}$$

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} < (M + fl_l) \qquad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \tag{2}$$

Combining learning-by-doing, training, and forgetting, we derive the following constraint:

$$z_{ilt} = z_{il(t-1)} + yt_{ilt} \cdot v_i + u_{ilt} - w_i \cdot fg_{ilt} \qquad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \tag{3}$$

With $fg_{ilt} \in \{0, 1\}$ and $y_{ilt} = \sum_{k=1}^{K} y_{iklt}$. The following constraints assure that workers only carry out production activities on those skill levels k that they have already achieved, with $r_{iklt} \in \{0, 1\}$.

$$z_{ilt} - z_{kl}^{min} \geq -M \cdot r_{iklt} \qquad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \tag{4}$$

$$y_{iklt} \leq M \cdot (1 - r_{iklt}) \qquad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \tag{5}$$

A company skill level target $\phi_i \leq \sum_{l=1}^{L} z_{ilT}$ needs to be satisfied by every employee i. The target is embodied in the model to assure that the skill development does not drop in the last period T and that company skill levels are sufficiently developed by the end of the planning horizon (Heimerl and Kolisch, 2010).

4.1.2 Budgeted Training Measures

To budget training measures, we introduce a training sessions limit $\overline{ucap_t}$ which restrains the total number of all training sessions for all production activities l and all employees i. We incorporate the following constraints into our model to analyze the effect of budgeted training and we omit these in the model not incorporating budgeting.

$$\sum_{i=1}^{m} \sum_{l=1}^{L} u_{ilt} \leq \overline{ucap_t} \qquad \forall t \in \{1, \dots, T\} \tag{6}$$

In order to prohibit training in certain periods t, the capacity $\overline{ucap_t} = 0$ can be chosen, resulting in $u_{ilt} = 0$ for the respective periods.

4.1.3 Demand

In every period t, a demand D_{jt} for product j has to be satisfied. As storage is not possible, a shortage of product j, defined as $sh_{jt} = D_{jt} - \sum_{l=1}^{L} (a_{jl} \cdot ys_{lt})$, may arise and is penalized with shortage costs sc_j per unit (with $ys_{lt} = \sum_{i=1}^{m} \sum_{k=1}^{K} y_{iklt}$). The variable a_{jl} defines the number of products j produced by production activity l. To simulate demand volatility, a randomization function is implemented in GAMS to create demand values for all periods and products depending on a given volatility level. The level of volatility determines an upper and lower boundary within which the demand can vary. Starting with a fixed demand

D and a volatility level $dv \in \{1, \dots, D\}$, the set of possible demand values is given by $D_{jt} \in \{D - dv, D - dv + 1, \dots, D + dv\}$.

4.1.4 Objective Function

We implement our Mixed-Integer-Program as a minimization problem, optimizing the total production costs over all periods $t \in \{1, \dots, T\}$. The total costs consist of production costs, training costs, and shortage costs.

$$\underbrace{\sum_{i=1}^{m}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{kl} \cdot y_{iklt}}_{\text{production costs}} + \underbrace{\sum_{i=1}^{m}\sum_{l=1}^{L}\sum_{t=1}^{T} c_l \cdot u_{ilt}}_{\text{training costs}} + \underbrace{\sum_{j=1}^{n}\sum_{t=1}^{T} sc_j \cdot sh_{jt}}_{\text{shortage costs}} \rightarrow \min \tag{7}$$

This model is developed to simulate the interplay of training measures, learning-by-doing, forgetting, and volatile demand. Therefore, it is not suited for operative workforce assignment in its current version.

4.2 Numerical Example

In our simulation, $m = 4$ employees can process $L = 3$ production activities each to produce one of the $n = 3$ products during $T = 18$ periods. During the ramp-up phase, the new production processes are introduced. For the sake of simplicity, we assume that all workers i start with the same competence level $z_{il0} = 30$ with respect to all production activities l. Employees can increase their competence level through learning-by-doing with an underlying learning rate $v_i = 1$ or through training. As described above, each training measure increases the skill units. A continuous scale of skill units is combined with $K = 4$ discrete skill levels which enable workers to perform production activities on a higher efficiency level, meaning that their production costs c_{kl} and time p_{kl} will decrease with a higher skill level k according to the following values:

$$p_{kl} = \begin{Bmatrix} 5 & 5 & 5 \\ 4.5 & 4.5 & 4.5 \\ 4.2 & 4.2 & 4.2 \\ 4 & 4 & 4 \end{Bmatrix}, c_{kl} = \begin{Bmatrix} 10 & 20 & 40 \\ 9 & 20 & 30 \\ 8 & 18 & 20 \\ 7 & 17 & 10 \end{Bmatrix}, sc_j = \begin{Bmatrix} 40 \\ 70 \\ 40 \end{Bmatrix}$$

The four skill levels are set as follows: Level one ranges from 1 until 50 skill units, level two starts with 50 skill units, level three with 200 skill units, and level four, the highest skill level, starts at 500 skill units. Workers with skill level four cannot improve their performance in the respective production activity any further. However, higher skill levels also prevent forgetting. It is not possible, though, for workers to exceed 2500 skill units in any production activity, i.e., $z_{ilt} \leq 2500$. The values for c_{kl} were chosen to allow for different learning patterns which might be driven by different levels of task complexity (Shafiei-Monfared and Jenab, 2011). For this purpose, a product produced with high efficiency gains due to learning

(l = 3), an s-shaped model (l = 2) with slow learning at the beginning (Baloff, 1971) and a moderate log-linear learning curve (l = 1), e.g. accounting for cognitive or manual tasks with high complexity (Dar-El et al., 1995; Shafiei-Monfared and Jenab, 2011), are employed in terms of production costs. Note that cost learning effects include effects from employee learning, such as material handling and waste reduction (Lapré et al., 2000), as well as effects from reengineering and adaptions in the productions processes which are prominent in the s-curve model (Baloff, 1971).

While learning-by-doing takes place during the production process and does not result in any further costs, two distinct kinds of training costs arise for training: on the one hand, the needed time tr_l = 5 and on the other hand, the monetary costs c_l = 2. The time utilized for training reduces the capacity available for production. Therefore, opportunity costs of lost production (shortage costs) arise. Forgetting occurs if an employee pursues a production activity or undergoes training fewer than fl_l = 10 times in a period. In the case of forgetting, the workers' competence units decrease by w_i = 10 units. The company skill target for the end of the planning horizon is ϕ_i = 500 skill units per worker.

Three features of the modeled production system factors are manipulated: the demand, employee capacities, and training availability. To simulate a stochastic demand, a random distribution of period demands is applied. After choosing a stochasticity (demand volatility) level *dv* from 1 to 100, a random algorithm sets demands D_{jt} for all products j so that they sum up to 5400 over all 18 periods per product. Different time capacity levels of employees are applied in order to analyze the intensity of the demand volatility relative to the workforce capacity. The aforementioned three scenarios use the following time capacity $\overline{CAP_i}$ per period: *low* = 200*, medium* = 375, and *high* = 550. These limits are chosen to simulate different impacts of demand volatility on production. In the low-capacity scenario, workers cannot meet the average demand of 100 units per period per product with their initial skill endowment. The medium-capacity scenario enables workers to meet the average demand exactly, while employees in the high-capacity scenario can meet the given demand and have additional capacity to be trained in each period.

The third manipulated factor is the budgeted training access. In the budgeted scenario, the training capacity limit for all employees together is set to $\overline{ucap}$ = 180 per period in the first five periods. The following periods 6 to 18 do not allow for training measures.

Combining those factors, we receive 100 datasets based on the volatility simulation for each capacity level and each scenario, with and without budgeted training measures, resulting in 600 datasets in total with 10,800 data points due to the 18 periods of observation.

To solve the above-described model, we utilize the Gurobi 7.5.2. solver in GAMS. We terminate the runs when a gap of 4% is reached. The dataset obtained serves as the basis for the analysis which is performed in the following section.

5 Results and Discussion

In the following a description of the applied analysis method in Section 5.1 and a descriptive analysis in Section 5.2 is presented. The section is hereinafter structured according to the hypothesis derived in Section 3. The influence of budgeting training measures on skill development is analyzed in Section 5.3. Further, we aim to shed light on the effects of demand volatility in Section 5.4 and, lastly, we analyze the interplay of budgeted training measures, the intensity of demand volatility, and employee capacity in Section 5.5.

5.1 Analysis Methodology

Throughout our analyses, *Generalized Estimating Equations* (*GEE*) are employed in order to investigate the effects of the above explained factors on the dependent variables and to test the previously formulated hypotheses. To do so, we used the open-source platform *R* (version 3.6.1) and the package *geepack* (Halekoh et al., 2006). Regression analyses with GEE are appropriate for the analysis of longitudinal data. Because of the normal distribution of the variables, we employ a *gaussian* family and use an *identity link*. Due to the time-dependent nature of our variables, we use an AR(1) structure (Ballinger, 2004). With regard to our previously formulated hypotheses, we use six dependent variables: *Training* (Table V–1), *Learning-By-Doing* (Table V–2) and *Forgetting* (Table V–3), as well as *Learning Output* = *Training* + *Learning-By-Doing* (Table V–4), *Total Skill Development* = *Training* + *Learning-By-Doing* −*Forgetting* per period (Table V–5) and, lastly, the *Achieved Skill Units*, which equal the sum of the achieved skill units over all activities for each period (Table V–6). The expression 'employees' skill development' utilized in the hypothesis focuses mainly on the variable *Total Skill Development*. Appendix V–2 links the six dependent variables to the simulation model.

The main explanatory variables are *Budget*, displaying whether training is budgeted *Budget* = 1 or whether unconstrained training is available *Budget* = 0, *Volatility* ranging from 1 to 100 in discrete steps, and *Capacity* taking values for the three capacity scenarios of 200 (low), 375 (medium), or 550 (high). Further, we include *Time* which reflects the periods during the planning horizon. For each dependent variable we conducted six GEE regressions displayed in Tables V 1 to 6.

The first three columns show models depicting the main effects only, i.e., on all 10,800 data points per variable and all capacity scenarios. The model in column 1 assumes a linear relationship between the employees' capacities. Similar to Letmathe and Schinner (2021), we find a non-linear relationship when analyzing the influence of employee capacity on training. We model this non-linear relationship by using a quadratic term for capacity and extend the models in columns two and three by the quadratic term $Capacity^2$ to better fit the quadratic u-shaped effects that we see in the data. Further, we compute the interaction variables *Volatility*Capacity*, *Volatility*Budget*, and *Budget*Capacity* to analyze the interplay of the manipulated variables and the capacity scenarios in more detail. The latter three models (columns 4-6) comprise the main effects for the different capacity scenarios separately. Throughout our analysis, we focus on significant effects only. The quadratic term $Capacity^2$ is significant in all models. Therefore, we analyze the effects displayed in the second column and omit analyzing the results in the first column, where a linear relationship is assumed. For the sake of completeness, we display the models without $Capacity^2$ in the first column.

5.2 Descriptive Analyses

Before turning to the results of the multivariate statistics and the tests of the hypotheses, we first report some descriptive results for a better understanding of the underlying strategies for how companies can most efficiently cope with learning and training requirements in the different scenarios. In Figure V–1, the average training measures undertaken by all workers per period are displayed. The number of training sessions decreases over time in both scenarios; nevertheless, training measures are initially used more frequently in the budgeted scenario than in the flexible scenario, where they decrease continuously. Due to the model's assumption, workers in the budgeted scenario cannot train later than in period 5, whereas workers in the flexible scenario can be trained in all periods.

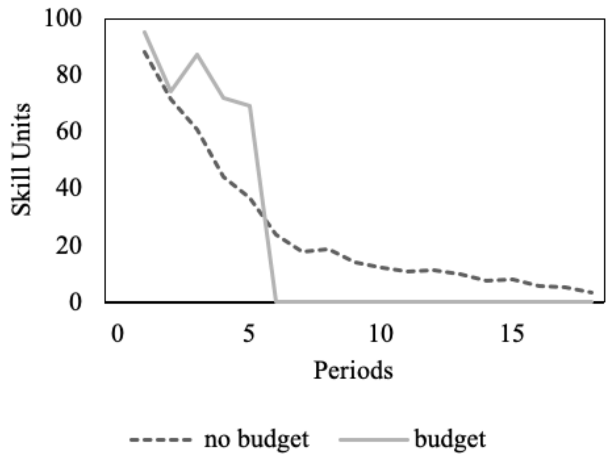

Figure V–1: Average Training per Period

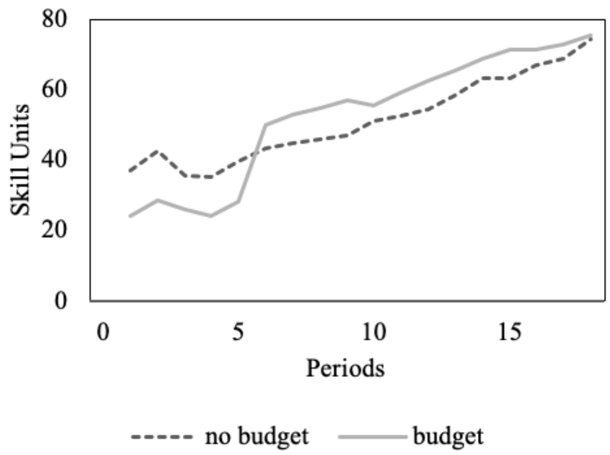

Figure V–2: Average Forgetting per Period

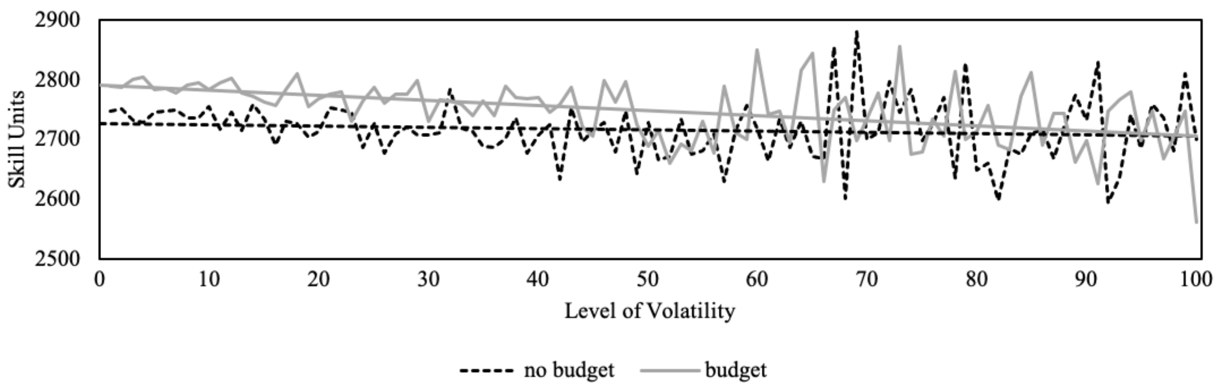

Figure V–3: Average Achieved Skill Level vs Volatility

Considering the development of forgetting, displayed in Figure V–2, we see a contradictory behavior, which aligns with the findings from the average training measures. Overall, forgetting increases over time in both scenarios. However, in the budgeted scenario, workers forget less knowledge in the first five periods of observation compared to the flexible scenario. In period six, this effect changes, as workers forget more acquired knowledge in the budgeted scenario. The effect of more training and fewer forgetting in the first five periods results in a generally higher level of average achieved skills in the budgeted scenario. In both scenarios, but more pronounced in the flexible scenario, employees can use their time endowment in periods of low demand for training and prepare for periods with higher demand. The effect that workers achieve higher average skill levels in the budgeted setting is especially strong in the settings with low to medium volatility (*Volatility* ≤ 60), shown in Figure V–3, and diminishes with higher volatility (*Volatility* > 60). Considering a volatility level of 100, the underlying trend lines of budgeting and flexible training merge. Thus, if volatility and capacity allow for training, workers are trained more intensively in the first five periods in the budgeted scenario compared to the flexible scenario. Hereby, the forgetting caused by missing training opportunities in the later periods is counterbalanced. Since our model does not allow to build up inventory, the excess employee capacity during low demand can solely be used for training. In the budgeted scenario, this is only possible in the first five periods. In later periods the capacity cannot be used to counteract forgetting by training measures. Consequently, in times of low demand and budgeting, the available capacity cannot be used for neither training nor production. This results in excess unused capacity due to the fluctuations in demand. This results in excess, unused capacity due to fluctuations in demand. However, excess capacity must still be maintained for periods of high demand. The dynamics are visualized in the Appendix for the different capacity scenarios (see Appendix V–3 to Appendix V–5).

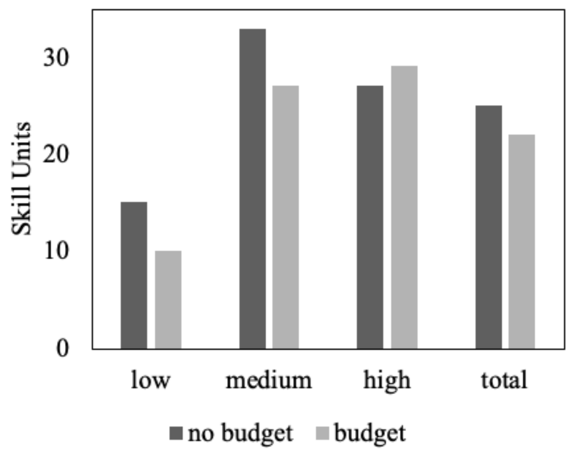

Figure V–4: Average Training per Capacity Scenario

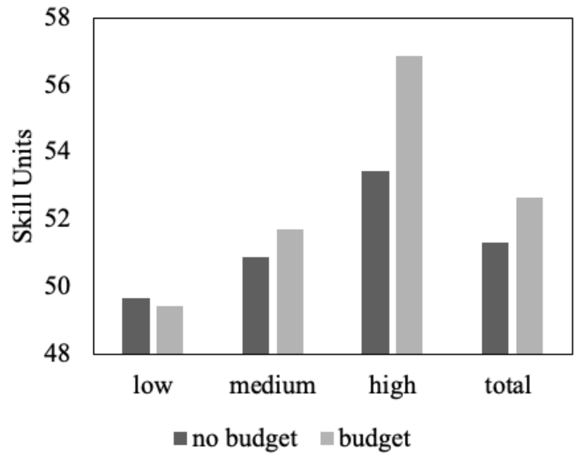

Figure V–5: Average Forgetting per Capacity Scenario

When turning to the three capacity scenarios, we find a difference in the absolute number of training measures (Figure V–4). By indicating an inverse u-shape curve, training is higher in the medium capacity scenario and somewhat lower in both other scenarios. The lowest amount of training measures is undertaken in the low-capacity scenario. Based on the u-shaped influence of the capacity endowments employed, we modeled capacity as a quadratic term $Capacity^2$ in our GEEs to test whether this relationship has a significant impact. Surprisingly, we find the number of average training sessions to be larger in the budgeted than in the flexible scenario, considering the high-capacity setting. Figure V–5 reveals that forgetting increases with higher capacity. This relation can be explained through more intensive training in the first periods due to the higher time capacities available. More initial training leads to more forgetting in later periods. Not surprisingly, this effect is more pronounced in the budgeted scenarios, where training is squeezed into the first periods of the planning horizon. Each of the following sections evaluates the individual effects of learning, training and forgetting first and turns later to the compound variables learning output, skill development and achieved skill levels.

5.3 Influence of Budgeted Training Measures

Focusing on the effect of budgeted training measures (*Budget*), we find evidence for the assumption that budgeting has a significant negative effect on *Training* ($p < 0.001$, column 2, Table V–1). In contrast to *Training*, *Learning-By-Doing* is positively affected by budgeting training measures ($p = 0.018$, column 2, Table V–2). This effect can only be observed when including capacity as a quadratic term *Capacity*^{2}, as it is only significant in the low-capacity scenario ($p < 0.001$, column 4, Table V–2) and vanishes with more employee capacity (columns 5 and 6, Table V–2). This might be driven by possible efficiency gains due to training which reduce shortage costs in later periods to an extend that allows missing the demand and paying shortage costs in earlier periods.

Table V–1: Coefficients from GEE Regression Training

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	50.866 ***	14.460 ***	28.992 ***	35.056 ***	90.424 ***	87.990 ***
Budget	-2.713 ***	-2.733 ***	-6.653 ***	-4.889 ***	-5.580 ***	1.053
Volatility	0.044 ***	0.042 ***	-0.182 ***	-0.069 ***	0.019	0.175 ***
Time	-4.858 ***	-4.852 ***	-4.850 ***	-1.729 ***	-6.130 ***	-6.906 ***
Capacity	0.052 ***	0.279 ***	0.237 ***			
Capacity^2		-0.0003 ***	-0.0003 ***			
Volatility*Capacity			0.001 ***			
Volatility*Budget			-0.049 **			
Budget*Capacity			0.017 ***			

* weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table V–2: Coefficients from GEE Regression Learning-By-Doing

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	127.368 ***	-88.072 ***	-87.746 ***	163.071 ***	300.047 ***	301.447 ***
Budget	0.196	0.572 **	2.409 ***	1.474 ***	0.172	-0.035
Volatility	-0.067 *	-0.062 ***	-0.086 ***	-0.023 ***	-0.163 ***	-0.0003
Time	0.773 ***	0.727 ***	0.727 ***	1.944 ***	0.374 **	-0.149
Capacity	0.339 ***	1.684 ***	1.683 ***			
Capacity^2		-0.002 ***	-0.002 ***			
Volatility*Capacity			0.00007 **			
Volatility*Budget			-0.002			
Budget*Capacity			-0.005 ***			

* weakly significant (p < 0.1), ** significant (p < 0.05), *** highly significant (p < 0.001)

Table V–3: Coefficients from GEE Regression Forgetting

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	18.183 ***	22.040 ***	20.717 ***	16.403 ***	33.647 ***	22.425 ***
Budget	1.209 ***	1.211 ***	-2.100 **	-0.324	0.669	3.390 ***
Volatility	0.026 ***	0.026 ***	-0.091 ***	0.085 ***	-0.038 ***	0.031 ***
Time	2.726 ***	2.726 ***	2.726 ***	3.050 ***	2.027 ***	3.101 ***
Capacity	0.016 ***	-0.008	-0.005			
Capacity^2		0.00003 ***	0.00003 ***			
Volatility*Capacity			-0.0002 ***			
Volatility*Budget			-0.012			
Budget*Capacity			0.011 ***			

* weakly significant (p < 0.1), ** significant (p < 0.05), *** highly significant (p < 0.001)

Table V–4: Coefficients from GEE Regression Learning Output

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	175.035 ***	-73.847 ***	-59.310 ***	198.155 ***	390.298 ***	383.761 ***
Budget	-2.515	-2.447 ***	-5.627 ***	-3.448 ***	-5.635 ***	1.842 **
Volatility	0.001	-0.029 **	-0.262 ***	-0.092 ***	-0.145 ***	0.142 ***
Time	-4.164 ***	-4.068 ***	-4.068 ***	0.211 ***	-5.723 ***	-6.645 ***
Capacity	0.404 ***	1.966 **	1.924 ***			
Capacity^2		- 0.002 ***	-0.002 ***			
Volatility*Capacity			0.001 ***			
Volatility*Budget			-0.045 **			
Budget*Capacity			0.015 ***			

* weakly significant (p < 0.1), ** significant (p < 0.05), *** highly significant (p < 0.001)

Table V–5: Coefficients from GEE Regression Total Skill Development

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	-157.039 ***	-95.782 ***	-79.911 ***	181.691 ***	356.584 ***	361.274 ***
Budget	-2.841	-3.595 ***	-3.570 **	-3.099 ***	-6.255 ***	-1.515 *
Volatility	-0.030	-0.055 ***	-0.354 ***	-0.178 ***	-0.107 ***	0.111 ***
Time	-6.831 ***	-6.787 ***	-6.787 ***	-2.832 ***	-7.748 ***	-9.745 ***
Capacity	0.384 ***	1.973 ***	1928 ***			
Capacity^2		-0.002 ***	-0.002 ***			
Volatility*Capacity			0.001 ***			
Volatility*Budget			-0.032 *			
Budget*Capacity			0.004			

* weakly significant (p < 0.1), ** significant (p < 0.05), *** highly significant (p < 0.001)

Table V–6: Coefficients from GEE Regression Achieved Skill Units

Variables	All Capacity Levels			Different Capacity Levels		
	linear	quadratic	interaction	low (200)	medium (375)	high (550)
Observations	*N = 10800*	*N = 10800*	*N = 10800*	*N = 3600*	*N = 3600*	*N = 3600*
Intercept	-896.802 ***	-3454.479 ***	-3222.401 ***	534.215 ***	642.943 ***	521.129 ***
Budget	5.111	17.789 **	0.802	5.875	-17.664	37.930 **
Volatility	-0.456	-0.488 ***	-4.627 ***	-2.102 ***	-1.213 ***	1.842 ***
Time	224.959 ***	223.649 ***	223.553 ***	142.324 ***	268.171 ***	263.153 ***
Capacity	3.861 ***	19.959 ***	19.312 ***			
Capacity^2		- 0.021 ***	-0.021 ***			
Volatility*Capacity			0.012 ***			
Volatility*Budget			-0.626 **			
Budget*Capacity			0.131 **			

* weakly significant (p < 0.1), ** significant (p < 0.05), *** highly significant (p < 0.001)

The missing effect in the higher capacity scenarios might be driven by the fact that there is sufficient capacity endowment to meet the given demand and to allow for the amount of training needed for preventing higher shortage costs in later periods. Consequently, companies produce equally in both scenarios to meet the given demand, which further fosters comparable results for *Learning-By-Doing*. The contradictory effects of *Training* and *Learning-By-Doing* result in an overall negative effect of *Budget* on the compound variable *Learning Output*, again with a non-linear and significant influence of the capacity endowments *Capacity*^{2} (p < 0.001, column 2, Table V–4). Turning to the three capacity levels, we find that in the low and medium scenarios the missing opportunities for training lead to a negative influence of *Budget* on the *Learning Output* (p < 0.001, column 4 and 5, Table V–4) whereas the budgeting leads to a positive effect in the high-capacity scenario (p < 0.001, column 6, Table V–4). This effect aligns with the findings of the descriptive analyses which show that employees undertake more training measures in the first periods in the budgeted scenario compared to the flexible scenario (Figure V–5). The amount of extra training sessions is high enough to exceed the training measures utilized in the flexible scenario in the whole planning horizon, and thus, lead to a significant positive learning output for budgeting in the high-capacity scenario as well as in the whole dataset. Analyzing the effect of *Budget* on *Forgetting* (Table V–3), we find that the absence of an all-time availability of training measures fosters the loss of workers' skill units significantly (p < 0.001, column 2 and 6 Table V–3). The change of sign of the effects of the variable *Budget* throughout the different capacities illustrates the non-linear and significant impact of the capacity variable $Capacity^2$ (p < 0.001, column 2, Table V–3). These findings are consistent with the assumption made by Jaber et al. (2003) that training measures might be used to keep skill units high and thus prevent forgetting.

When looking at the overall effect on the *Total Skill Development* (Table V–5), which includes *Training*, *Learning-By-Doing* and *Forgetting*), we find a significant negative impact of budgeted training measures (*Budget*) with a non-linear and significant impact of the capacity endowment $Capacity^2$ (p < 0.001, column 2, Table V–5). This negative impact persists in all scenarios while being only weakly significant in the high-capacity scenario (p < 0.001, column 4, 5 and 6, Table V–5). This shows that extensive training in the first periods allows compensating the effect of forgetting in the later periods. Consequently, the results support H1, as the budgeting of training measures has a negative impact on skill development.

Surprisingly, the data reveal a positive effect of *Budget* on the overall *Achieved Skill Units* (p < 0.001, column 2, Table V–6). This effect depends on the non-linear influence of the capacity and can only be observed in the high-capacity scenario. However, this effect is no longer significant when the relevant interaction effects are considered (p = 0.9667, column 3, Table V–6). Thus, H1 is supported. Therefore, we now turn to the hypotheses to investigate the relevant effects triggered by our two manipulated variables – demand *Volatility* and employee *Capacity*.

5.4 Influence of Volatility

Hypothesis H2 proposes that demand volatility has a negative impact on employees' skill development. Again, we look at the individual effects of *Training*, *Learning-By -Doing*, and *Forgetting* first, and then consider the total effect on employee skill development. Surprisingly, we find that demand *Volatility* has a small but significant (p < 0.001, column 2, Table V–1) positive impact on workforce *Training.* Analyzing the capacity scenarios, we find contradictory results. The impact of *Volatility* in the scenario with high demand intensity (low-capacity) is significant negative ($p < 0.001$, column 4, Table V–1), not significant but positive in the medium scenario, and significant positive ($p < 0.001$, column 6, Table V–1in the scenario with low demand impact (high-capacity). This effect is probably driven by the fact that high volatility at low capacity leads to high shortage costs, as the corresponding demand cannot be met when employees are trained extensively. At high capacity, the volatility can be absorbed and it is further possible to invest excess time in the training of the workers. Again, this effect on *Training* is accompanied by a non-linear and significant influence of *Capacity*^{2} ($p < 0.001$, column 2, Table V–1), *Learning-By-Doing* is affected negatively by *Volatility* ($p < 0.001$, column 2, Table V–2). This effect persists in the low and medium capacity scenarios ($p < 0.001$, column 4 and 5, Table V–2). Employees are not able to meet the high demand which is strongly deviating from the average if high demand volatility is employed. This might affect especially the first periods, where no experience gains are present, caused by the time capacity restrictions. Additionally, we do not include storage in our model and it is impossible to produce goods in advance to meet later demand. Thus, production opportunities are forgone and *Learning-By-Doing* decreases with respect to a scenario with lower demand volatility. Moreover, an explanation for this might be, for example, that volatility leads to workers frequently having to change tasks, which means that specialization potential cannot be fully exploited. As a result, increases in skill levels through *Learning-By-Doing* are lower when volatility is high and can only be buffered by excess capacity in the high-capacity scenario in which *Volatility* has no effect (column 6, Table V–2). Considering the combined variable *Learning Output* (Table V–4), *Volatility* has a negative influence. In the low- and medium-capacity scenarios, the effect is significant negative. In the high-capacity scenario, again, training measures can be used in times of low demand to prepare for times with higher demand. Thus, a positive effect occurs ($p < 0.001$, columns 4,5 and 6, Table V–4).

Similarly, we find significant positive effects on *Forgetting* due to *Volatility* ($p < 0.001$, column 2, Table V–3), as workers miss opportunities for *Learning-By-Doing* and training, which both may prevent forgetting. Interestingly we find a significant non-linear effect of *Capacity*^{2} ($p < 0.001$, column 2, Table V–3) which is reflected by a u-shaped effect in the different capacity scenarios, since the effect of *Volatility* on *Forgetting* is positive in the scenarios with low and high capacity ($p < 0.001$, columns 4 and 6, Table V–3), whereas *Forgetting* decreases with higher volatility in the medium scenario ($p < 0.001$, column 5, Table V–3). This at first glance contradictory result can be interpreted by looking at various influence factors. *Volatility* at low capacity leads to frequent changes of tasks among the employees and thus to less specialization and more forgetting. The increase in forgetting at high capacity on the other hand can be explained by the fact that more knowledge is built up and thus the possibilities of forgetting increase. The medium-capacity scenario, on the other hand, might use a good mix of specialization and training. Therefore, more volatility does possibly not lead to more forgetting here, but on the contrary to significant higher retention of the skills once they have been acquired.

For *Total Skill Development* (column 2 Table V–5) and *Achieved Skill Units* (column 2, Table V–6), we observe negative effects with increasing deman*d Volatility*, similarly to the individual effects described above. This effect is visualized in Figure V–3. Hence, we find support for our second Hypothesis H2 in the whole data set ($p < 0.001$, column 2, Tables 5 and 6), as well as in the low and medium capacity scenario ($p < 0.001$, column 4 and 5, in Tables 5 and 6). Nevertheless, in the high-capacity scenario, we find a significant positive effect of increasing demand *Volatility* on the *Total Skill Development* ($p < 0.001$, column 5, Table V–5) and the *Achieved Skill Units* ($p < 0.001$, column 5, 6). After discussing the results for the individual effects, this result should no longer be surprising.

5.5 Interaction Effects with Budgeting

First, we present the interaction effect between budgeting training measures and employee capacity. Second, we analyze the interaction between demand volatility and budgeting.

Since employees' time capacity is used for training and production, the effect of budgeting on skill development depends on employees' capacity endowment. The importance and effect of the capacity scenarios have already emerged from the presented analyses, which further emphasized the importance of the non-linear effect. These effects are underlined by a significant influence of the quadratic term $Capacity^2$ on all variables. In order to gain further insight on the influence of the moderating variable *Capacity* in combination with budgeting, we compute the interaction effect of *Budget∗Capacity* on the variables describing employees' skill development. Analyzing the effect of the interaction variable on *Training* measures, we find a significant positive effect ($p < 0.001$, column 3, Table V–1). The effect supports H3 and indicates that employees practice more during the initial periods if excess capacity (high-capacity scenario) is available and shortage costs can be kept at their minimum. These extra training measures might be connected to costs for the company, at least in terms of employee capacity.

For *Learning-By-Doing*, we find a significant negative effect for the interaction of budgeting and capacity *Budget∗Capacity* ($p < 0.001$, column 3, Table V–2). Interestingly, we find a positive interaction effect of *Budget∗Capacity* on *Forgetting* ($p < 0.001$, column 3, Table V–3), indicating that excess capacity leads to more forgetting. In this vein, Figure V–4reveals that workers lose relatively and absolutely more skill units due to forgetting in the high-capacity scenario. On the one hand, the high employee capacity endowment allows for tactical training, in order to prevent forgetting in the flexible scenario. On the other hand, the plot on the right (Figure V–5) shows that in the budgeted high-capacity scenario, absolutely more training measures are used, compared to the flexible setting. This is noteworthy, as training is only possible in the first five periods. Thus, employees are initially trained to a higher skill level in the high-capacity scenario, which consequently results in more forgetting and is driven by the aim to avoid shortage costs in later periods.

Considering the compound variable *Learning Output*, the interaction variable *Budget∗Capacity* has a significant positive effect ($p < 0.001$, column 3, Table V–4), driven by the effect on *Training* ($p < 0.001$, column 3, Table V–1). However, the data do not reveal a significant effect on the *Total Skill Development*, which incorporates *Forgetting* and thus a complementary effect to *Training*. Relating to the *Achieved Skill Units* of employees, we observe a significant positive interaction of *Budget* and *Capacity* ($p = 0.0022$, column 3, Table V–6). These results provide partial support for H3. The achieved skill units are positively affected, as employees are initially trained to a higher skill level in the budgeted scenario in order to use the initial productivity gains as a buffer against future volatility and forgetting. Therefore, the total skill development per period is not positively affected as the higher achieved skill units decrease over time due to an increase in forgetting compared to scenarios without volatility. In this vein, employees do gain more skill units in absolute terms which are lost in the consecutive periods. Thus, this effect must be treated with caution.

Turning to the effect of the interaction variable *Volatility∗Budget*, which combines budgeting and volatility, we find a negative and significant impact on *Training* ($p = 0.003$, column 3, Table V–1). On the one hand, this result might again be driven by the shortage costs which arise if production does not meet demand. Thus, production (reflected by the variable *Learning-By-Doing*) is prioritized over *Training* and is not further affected by the combination of budgeting and volatility (column 3, Table V–2). On the other hand, higher demand in the first periods does not only lead to unmet demand for the budgeted and flexible scenarios but moreover to foregone training opportunities in the budgeted scenario which cannot be offset in later periods. Thus, *Volatility∗Budget* amplifies the negative influence of *Training*. Since it is not possible in the budgeted scenario to compensate for forgetting through training measures in the budgeted scenario any later than in period five, demand volatility in combination with budgeting does not have any further significant effect on *Forgetting* (column 3, Table V–3). As a result, we receive a negative and significant impact on *Learning Output* (p = 0.014, column 3, Table V–4), *Total Skill Development* (p = 0.082, column 3, Table V–5) and *Achieved Skill Units* (p = 0.0065, column 3, Table V–6). Therefore, hypothesis H4 is supported and we do find a negative influence of the interaction variable *Volatility∗Budget* on the employees' skill development. Due to the fact that the interaction variable *Volatility∗Capacity* has extensively been studied by Letmathe and Schinner (2021), we omit analyzing this relation. Since the effects were significant in their study, we included the variable for the sake of completeness so that we could analyze the remaining effects in a more differentiated manner.

6 Conclusions

Summarizing our analyses of traditional (budgeted) versus flexible training approaches on production ramp-up under the influence of demand volatility and different employee capacity endowments, we find that the budgeting of training measures has a negative influence on the skill development of employees. In detail, employees are trained less frequently and lose more skill units due to forgetting when training measures are budgeted. This is reflected by an overall lower average skill development of the workforce compared to flexible training approaches. Moreover, employees achieve higher skill units in the budgeted scenario, as excess training measures in the first periods can be used to compensate for forgetting in later periods. Thus, additional costs for initial training arise. To simulate different intensities of demand volatility, three scenarios with different time capacity endowments of workers are employed. In the low-capacity scenario, workers cannot meet the average demand per period using their initial time endowment. Thus, skill improvements through training and learning-by-doing are necessary for workers to meet the demand in later periods and to prevent shortages. The time endowment in the medium-capacity scenario is sufficient to meet the average demand but does not leave much time for training. In the high-capacity scenario, training and production are simultaneously possible. These three scenarios allow for an extensive analysis of the training impact on employees' skill development, depending on the products' demand and its volatility. When looking at the interplay of budgeted training measures and capacity, we find distinctive effects, which can be explained by different influence factors. Considering employees with a small capacity endowment, respective to demand, assignments to training or production are mainly driven by the need to fulfill a given demand and to prevent shortage costs. In the high-capacity scenario, on the other hand, the buffer effect predominates, i.e., the negative effects of demand volatility can largely be offset by the available overcapacity.

Therefore, the influence of budgeting is strongest in the low-capacity scenario, as employee training has to be squeezed into the few available time windows, and initial training in the first periods is often not possible. Consequently, the impact diminishes with higher capacity. Thus, the skill development and the achieved skill levels, increase with capacity. If employee capacities suffice, workers are trained extensively in the first periods to reach higher average skill levels allowing for lower costs and higher productivity in subsequent periods. Overall, the amount of training in the first five periods in the budgeted scenario is much higher than the number of training sessions in the flexible scenario, where workers can be trained at all times.

As a consequence, decisions on employee training need to be based on the employees' time capacity in relation to product demand. In times of high demand pressure, flexible training measures contribute to the skill development of employees, they prevent forgetting, and they offer higher efficiency gains. With enough employee capacities, it is possible to reduce negative effects by training employees to a higher extent than is needed in the first periods. Therefore, an investment in flexible training measures that can be used in times of low demand, e.g., e-learning or mobile learning, can potentially contribute to a company's productivity if employee capacities are fully utilized for meeting a given demand. Moreover, it can prevent costs for excess training measures undertaken in the first period which would not be necessary if employees have access to training when it is needed in order to prevent forgetting during all periods.

In summary, our research provides interesting insights into the interplay of employee learning, budgeting training measures, capacity restrictions, and demand volatility, which are also highly relevant in practice. The selected simulation scenarios make it possible to predict relevant interactions as a consequence of induced changes in the variables without making claiming general transferability of the results. Like any research, this article therefore has its limitations. Considering the results of our study, it should be noted that the used parameters were set by the researchers. Although these are derived using empirical results from the field and a former study by the authors, future research might validate the results using real shop floor data. Moreover, future research might include a setting that incorporates more employees and more tasks, or analyze the impact of flexible capacities to include overtime hours. The model considers categorical skills but assumes that each worker is able to perform any of the activities with her or his initial skill set. An extension to the study could model categorical skills in a way that demands employees to gain initial experience on the production task in order to be able to perform it. In this vein, effects of budgeted training measures on specialization and cross-training of workers could be evaluated. The production environment considered is a parallel production setting yielding multiple products. Analyzing the effects for serial production lines, i.e., assembly lines, provides further avenues for research.

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Appendix

Appendix V–1: Mathematical Model

$i \in \{1,\ldots,m\}$	denote the set of shop floor employees
$j \in \{1,\ldots,n\}$	products
$t \in \{1,\ldots,T\}$	period of the observation
$k \in \{1,\ldots,K\}$	discrete skill levels
$l \in \{1,\ldots,L\}$	production activities
a_{lj}	number of units of product *j* produced after pursuing production activity *l*
$\overline{CAP_i}$	time capacity of employee *i* in every period
c_{kl}	production costs per unit for activity *l* at skill level *k*
c_l	costs per training measure for production activity *l*
D_{jt}	demand for product *j* in period *t*
fg_{ilt}	binary variable displaying if forgetting occurs for employee *i* and production activity *l* in period *t*
fl_l	minimum amount of newly gained skill units in a period needed to prevent forgetting for activity *l*
M	*big M*
p_{kl}	processing time per unit for activity *l* at skill level *k*
r_{iklt}	binary variable displaying if employee *i* is able to pursue production activity *l* at skill level *k* in period *t*
sc_j	shortage costs of product *j*
sh_{jt}	amount of shortage of product *j* in period *t*
tr_l	time needed for one unit of training for production activity *l*
u_{ilt}	total amount of training measures of employee *i* in period *t* for production activity *l*
v_i	individual linear learning or skill development factor of employee *i*
w_i	individual factor for forgetting of employee *i*
y_{iklt}	amount of product *l* produced by production activity *k* by worker *i* in period *t*
yt_{ilt}	amount of all production activity *l* performed by employee *i* in period *t*
ys_{lt}	amount of all production activity *l* in period *t*
z_{ilt}	skill units of employee *i* for production activity *l* in period *t*
z_{kl}^{min}	required skill minimum
ϕ_i	company skill level target of employee *i* in period $t = T$

$$\sum_{i=1}^{m}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} c_{kl}\cdot y_{iklt} + \sum_{i=1}^{m}\sum_{l=1}^{L}\sum_{t=1}^{T} c_l \cdot u_{ilt} + \sum_{j=1}^{n}\sum_{t=1}^{T} sc_j \cdot sh_{jt} \rightarrow \ min \tag{1}$$

$$yt_{ilt} + u_{ilt} + M\cdot fg_{ilt} \geq fl_l \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{2}$$

$$yt_{ilt} + u_{ilt} + M\cdot fg_{ilt} < (M + fl_l) \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{3}$$

$$z_{ilt} = z_{il(t-1)} + yt_{ilt}\cdot v_i + u_{ilt} - w_i \cdot fg_{ilt} \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{4}$$

$$\sum_{k=1}^{K}\sum_{l=1}^{L} p_{kl}\cdot y_{iklt} + \sum_{l=1}^{L} tr_l \cdot u_{ilt} \leq \overline{Cap_i} \qquad \forall i \in \{1,\ldots,m\}, t \in \{1,\ldots,T\}. \tag{5}$$

$$z_{ilt} - z_{kl}^{min} \geq -M\cdot r_{iklt} \qquad \forall i \in \{1,\ldots,m\}, k \in \{1,\ldots,K\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{6}$$

$$y_{iklt} \leq M\cdot(1 - r_{iklt}) \qquad \forall i \in \{1,\ldots,m\}, k \in \{1,\ldots,K\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{7}$$

$$\phi_i \leq \sum_{l=1}^{L} z_{ilT} \qquad \forall i \in \{1,\ldots,m\} \tag{8}$$

$$\sum_{i=1}^{m}\sum_{l=1}^{L} u_{ilt} \leq \overline{ucap_t} \qquad \forall t \in \{1,\ldots,T\} \tag{9}$$

$$sh_{jt} = D_{jt} - \sum_{l=1}^{L} a_{jl}\cdot ys_{lt} \qquad \forall j \in \{1,\ldots,n\}, t \in \{1,\ldots,T\} \tag{10}$$

$$ys_{lt} = \sum_{i=1}^{m}\sum_{k=1}^{K} y_{iklt} \qquad \forall l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{11}$$

$$yt_{ilt} = \sum_{k=1}^{K} y_{iklt} \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{12}$$

$$fg_{ilt} \in \{0,1\} \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{13}$$

$$r_{iklt} \in \{0,1\} \qquad \forall i \in \{1,\ldots,m\}, k \in \{1,\ldots,K\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{14}$$

$$u_{ilt} \geq \ 0 \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{15}$$

$$y_{iklt} \geq 0 \qquad \forall i \in \{1,\ldots,m\}, k \in \{1,\ldots,K\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{16}$$

$$yt_{ilt} \geq 0 \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{17}$$

$$ys_{lt} \geq 0 \qquad \forall l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{18}$$

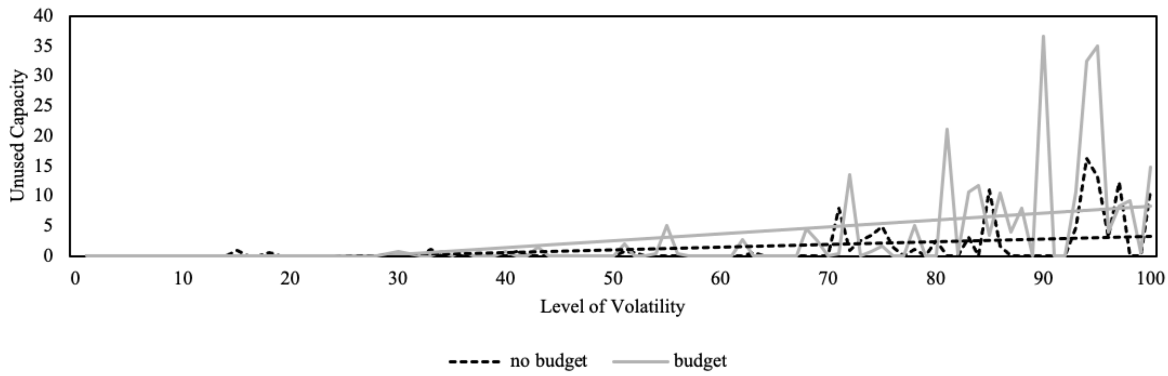
$$sh_{jt} \geq 0 \qquad \forall j \in \{1,\ldots,n\}, t \in \{1,\ldots,T\} \tag{19}$$

$$z_{ilt} \geq 0 \qquad \forall i \in \{1,\ldots,m\}, l \in \{1,\ldots,L\}, t \in \{1,\ldots,T\} \tag{20}$$

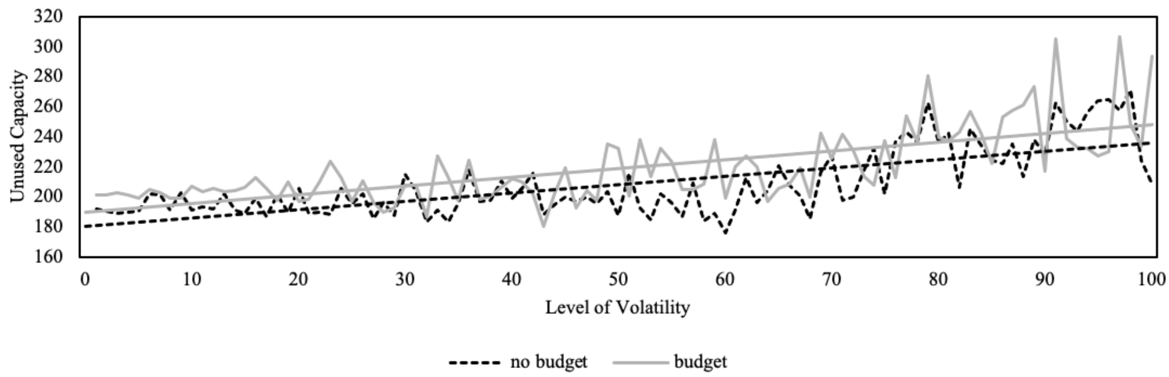
Appendix V–2: Mathematical formulation of the dependent variables

Learning-By-Doing	$= \sum_{i=1}^{m} \sum_{l=1}^{L} yt_{ilt} \cdot v_i$	$t \in \{1, \dots, T\}$
Training	$= \sum_{i=1}^{m} \sum_{l=1}^{L} u_{ilt}$	$t \in \{1, \dots, T\}$
Learning Output	$= \sum_{i=1}^{m} \sum_{l=1}^{L} yt_{ilt} \cdot v_i + \sum_{i=1}^{m} \sum_{l=1}^{L} u_{ilt}$	$t \in \{1, \dots, T\}$
Forgetting	$= \sum_{i=1}^{m} \sum_{l=1}^{L} w_i \cdot fg_{ilt}$	$t \in \{1, \dots, T\}$
Achieved Skill Units	$= \sum_{i=1}^{m} \sum_{l=1}^{L} \sum_{t=1}^{T} z_{ilt}$	
Total Skill Development	$= \sum_{i=1}^{m} \sum_{l=1}^{L} yt_{ilt} \cdot v_i - \sum_{i=1}^{m} \sum_{l=1}^{L} w_i \cdot fg_{ilt} + \sum_{i=1}^{m} \sum_{l=1}^{L} u_{ilt}$	$t \in \{1, \dots, T\}$

Appendix V–3: Unused Capacity – Cap 200 Low



Appendix V–4: Unused Capacity – Cap 375 Medium



Appendix V–5: Unused Capacity – Cap 550 High