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PROCESS MANAGEMENT OF ERGONOMIC WORKPLACE BASED ON AUGMENTED REALITY PRINCIPLES

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Abstract: *Ergonomics is an important element of managing performance and productivity in a company. Nowadays, the ergonomic parameters are set in line with the implementation of the Industry 4.0 concept. The paper highlights the link between virtual reality (VR) and augmented reality (AR), when combined with the traditional ergonomic procedure. Automation and digitization contribute to a significant extent to the creation of ergonomic workplaces and the elimination of the negative effects of non-ergonomic workplaces on people. The aim of the paper is to determine the essential elements of the system process approach to ergonomics management. This is achieved through an analysis of the current approaches from Industry 4.0 and a focus on the augmented reality approach. The backbone of the triple combination of "man-machine-environment" determines the ergonomic setting of work and the workplace. Subsequently, the presented case study examines the link between ergonomic workplace principles and data analytics for VR/AR technology. The scientific contribution of the paper lies in the discussion of the case study results, which is beneficial for the ergonomic design of workplaces.*

Keywords: *augmented reality, virtual reality, ergonomics, Industry 4.0, nine pillars of Industry 4.0.*

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INTRODUCTION

Today, the whole world is struggling with the widespread adoption of Industry 4.0. This trend is mainly characterized by the implementation of advanced technologies and devices such as robotics, co-botics, automation, 3D virtual reality and many more (LIAO, 2016; Valentina, 2021; May, 2019). Technologies available within Industry 4.0 can be divided into different categories. Some authors (Bona, 2021; Sari, 2020) believe that Industry 4.0 is based on nine key technologies, the so-called 9 pillars:

1. Industrial Internet of Things (IIoT)
2. Big Data
3. Horizontal and vertical integration of systems
4. Simulations
5. Clouds
6. Augmented reality
7. Autonomous robots
8. 3D printing
9. Cyber Security

A similar view is shared by Liagkou (2021), who adds other, more and lesser known, technologies in his article, such as cyber-physical system (CPS), artificial intelligence (AI) and/or mobile cloud. In contrast, Bai (2020) divides technologies into physical and digital ones. Among the physical technologies, he includes, for example, additive manufacturing, sensors or the use of drones. On the other hand, the digital group is more about information and communication technologies or software solutions, such as clouds, big data or 3D simulations. These technologies are described in more detail in subsection 2.1: Nine Pillars of Industry 4.0

However, it is not only technologies and modern devices, but also general research and development that is experiencing a constant rise. Resende (2021) and Ozdemir (2018) even suggest new products and technologies for an imaginary fifth industrial revolution (Industry 5.0), mainly under the umbrella of artificial intelligence (AI).

But the question remains, why do companies want to implement these modern technologies and conveniences? The most common reason is the desire to continuously improve productivity and efficiency of production processes, while continuously reducing costs within the nVA and Waste category. A second, less well-known reason is the ever-increasing pressure on production from customers (Lenart-Gansiniec, 2019; May, 2019). It is important to note that currently the end customer is identified with two forms. The primary and quite fundamental form is that the customer brings valuable funds to the company + is willing to buy in larger volumes or even more frequently if satisfied with the product/service. At the same time, in case his needs are satisfied, he is further willing to talk about the product/service to other people and thus increase the awareness of this advantageous purchase in the general public (Lee Chen, 2019). This customer image is quite intuitive and natural. However, in recent years, the customer has been given a second form that puts most manufacturing companies in a very uncomfortable position. This image can be defined as the desire of each individual to be original compared to others. In other words, in the context of any product purchase, the customer now presents himself as original and demands this originality or uniqueness from the product he buys. In practice, this means that new and new sub-processes are constantly being added to the main production process to cover this variability on the part of customers. Unfortunately, this also puts a lot of pressure from companies on their employees, who now have to be more and more skilled, productive without possible poor quality (Shahnazari, 2019; Lee Chen, 2019; Nascimento, 2019). And for this reason, Ergonomics exists and is being implemented, which in this fast-paced era seeks to optimize work and the workplace so that people can perform at their best while minimizing potential health risks and illnesses (Kadir, 2019; Sgarbossa, 2020). The author (Valentina, 2021) warns against this pressure on companies causing the human being, the cornerstone of Value creation, to be eliminated by technological conveniences. On the contrary, (Enrique, 2021) argues that the desire to implement modern technologies in production is mainly due to the flexibility that allows companies to respond in a timely manner to customer demand, while maintaining short production times without excessive costs and remaining competitive at all times.

Companies are therefore now at a point where they need to conduct a thorough analysis of their production processes and identify potential bottlenecks and risks that may affect both performance and operator health in the long term. At the same time, it is crucial for companies to find out what their customers demand and how best to meet their needs in quantity, quality and time.

It is for this reason that this article has been created, which focuses on ergonomics and seeks to find new modern ways in which companies can address the current issues mentioned above. The entire article is divided into four parts. In the first part, the Fourth Industrial Revolution will be briefly introduced along with iconic technologies (Bona, 2021; Bai, 2020). The second part is dedicated to contemporary ergonomics, which mostly uses augmented reality or simulations to improve working conditions. The third part is devoted to a case study in which the possible implementation of the mentioned technologies is depicted along with their impact. The last fourth part is dedicated to the author's thoughts and ideas about future work.

1. ERGONOMICS AND INDUSTRY 4.0 CONCEPTS

Ergonomics is the scientific discipline, oriented on the optimal interactions between human and other system attributes or components. Based on the data analytics design the human well-being system performance. Optimal coexistence of human and machine is principal change for new era of digitized production systems. Therefore, the implementation of Industry 4.0 should result in a spontaneous transformation into a Smart factory (Wang SY, 2016; Li XM, 2017; Chen BT, 2018).

Bona (2021) defined 9 key pillars of Industry 4.0 while (Bai, 2020) believes that the technologies associated with Industry 4.0, can best be divided into two categories - physical and digital. Both of the above approaches are best explained by (LI XM, 2017) who divides the Industry 4.0 architecture into four layers, namely: physical, network, cloud/big data and application layers. Figure 1 presented the basic architecture of Industry 4.0. (LI XM, 2017) with devices, robots, cobots, mobile devices, AGVs, as well as workers whose main goal is to perform given tasks the network layer, can be seen as an intermediary that transfers data in real time, either within a given layer (e.g., physical layer - machine-to-machine or human-to-machine/device data transfer) or across layers (physical layer data transfer through the network to cloud storage). The third layer is the aforementioned cloud/big data, whose main task is the storage and subsequent evaluation of the collected data. The last one is the application layer. This is where the individual entities in the form of smart companies, cities, users and services work with the processed data as they see fit.

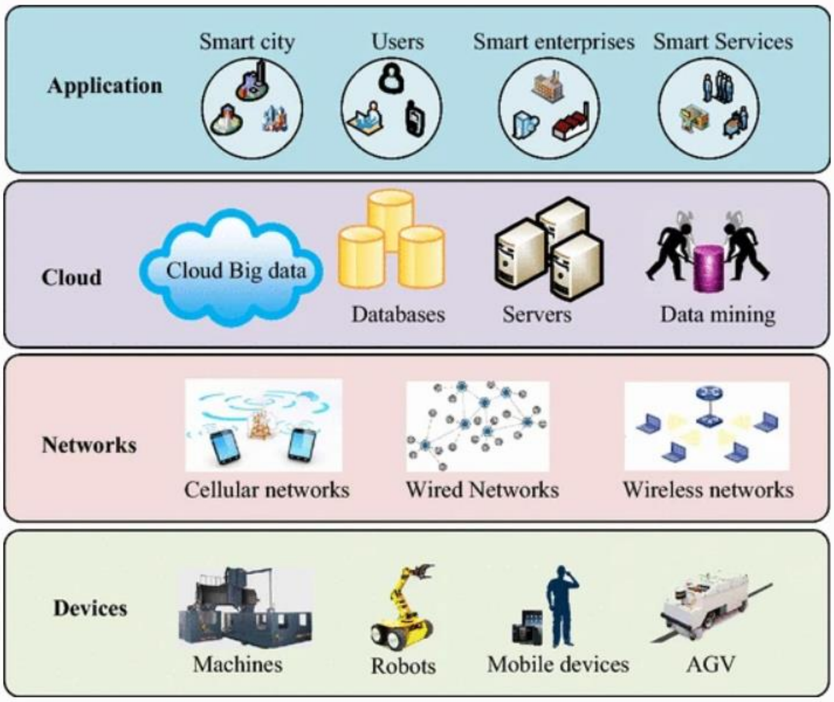


Figure 1. Basic Industry 4.0 Architecture (LI XM, 2017)

1.1. Core pillars of I 4.0 architecture

Industrial internet of things (IIoT) - refers to a type of IoT that was primarily created for industrial use, it connects individual objects and devices within the production system. According to (R.M. Alguliyev, 2019; Sisinni E., 2018) IoT contains functions as generation of the big data stream, multilevel data storage, real time processing, big data analytics, forecasting, control and management. IIoT architecture consist of physical layer, the communication layer, and the application layer (Yli-Ojap., 2019; Alladi T., 2019). The physical layer contains all the physical devices in the system such as production equipment, sensors, actuators, and data centres. The communication layer protects the communication between the actuators and the wireless sensor networks using (WSN), 5G, and machine to machine (M2M). According to (Wan Jf., 2016) it is possible to specify another layer, which can be professionally referred to as “Industrial Cloud”. This unique layer plays a key role because it stores a massive amount of data, but also serves as a computer technology when creating optimization and decision algorithms. These mentioned layers form the so-called CPS, which can be freely translated as a cyber-physical system. Based on CPS and the context of IIoT, the application layer is used for the development and creation of intelligent production systems.

Big Data - a concept dedicated for collection of various data from relevant sources and integration into the pre-defined databases (LI Shuyang, 2019). Big data are based on 3 variables: volume, variety and velocity (Wang, 2016; Chen Min, 2014; LI Shuyang, 2019). Volume be understood as the total volume of data, which usually ranges from terabytes (TB) to petabytes (PB). Variety indicates how diverse or diversified the data is. Velocity represents a rate of generated way of data processing. The authors (Zhong, 2017; De Mauro, 2015) extended this original concept by adding two more features, namely verification and value. While verification is not the same indicator as the previous ones mentioned, but rather it is a process to verify the quality of the collected data and to determine whether it is useful. It is important to note that when collecting data of such volume and velocity, there is also spontaneous collection of inappropriate/bad data and noise that must be separated from valuable data. The last and most important element according to (Kirms, 2019) is value, which identifies the actual utility that can be derived from this huge amount of data. Unfortunately, this process can be more complex if the data obtained faces three basic problems. The first problem arises if the data has been, in any way, affective by the previous four elements, and therefore it is not possible to clearly demonstrate the value of the data obtained. Secondly, it is quite challenging to examine the advantages/disadvantages or knowledge in the industry. The last problem is dedicated to the great difficulty in measuring the value of reports, statistics and decisions from big data due to the great influence of micro and macro aspects. However, (LI Shuyang, 2019; Talha, 2019) rely on the so-called "5Vs" in their articles, which add another element (volume, velocity, variety, value) in addition to the above four elements (volume, velocity, variety, value), which is veracity, which tries to reveal the real reliability and consistency of the data.

Horizontal and vertical integration of systems - is one of the key elements of Industry 4.0 (Lukoki, 2020). It deals with the interactions between particles (entities) that are at the same level. In manufacturing, these entities are most often, for example, machines that continuously collect data that is further shared among other entities for cooperative interaction. In contrast, vertical integration describes the relationships between the different layers of a system within a corporate hierarchy (Lukoki, 2020; Csalodi, 2021; Schmied, 2021). Through this integration, companies are able to transfer valuable information across departments and thus are able to more easily orchestrate individual operations, plan a given production and organize human work as it is needed. On the other hand, the author (Sony, 2017) perceives in his article that Industry 4.0 in terms of integration is not built on two types but on three. This third type is the so-called end-to-end engineering, which makes it possible to create customer friendly products or services. This is a process in which the individual requirements and needs of the customer are taken into account, which are then translated into research and development of the desired product/service.

Simulation - the ability to transfer real environment including real data (provided by machines, robots and other electronic devices) where the user can modify the given reality according to their needs or requirements and thus test (simulate) how a given workplace or work process is flexible to a specific change (Forcina, 2021; Fonseca, 2021). The result of simulation gives the possibility to see what advantages/disadvantages are related to the new solution to a specific problem (OEE, productivity, lost time, etc.). This way of verifying the correctness of the chosen solution is becoming more and more popular among companies because it helps to save all available valuable resources (money, time, human labour, energy, machine time, etc.).

Clouds - technology goes hand in hand with Big data technology which generates a huge amount of data that can be further processed through cloud computing (Cakmakci, 2019; Canas, 2021). The cloud computing architecture was the cornerstone of the new system, which was directly designed to meet the needs of any kind of manufacturing. Technology of Cloud Manufacturing (CMfg) manage the collected data through the internet and further use it to continuously accelerate their flexibility towards customer requirements. Simeon (2019) introduces the detailed concept of CMfg, which collects requirements from individual customers and also collects individual bids from suppliers. Thus, due to the built-in algorithm, this technology is able to identify the best possible solutions to meet the customers' needs in time and with the required quality. This concept has been extended by (Milosevic, 2019) who in his work described seven basic advantages of CMfg which are:

- Efficient use and sharing of resources
- Ability to implement quickly
- Frequent innovation
- Cost reduction
- Ability to level up
- Increasing productivity
- Quality

In contrast, (Kaynak, 2020) takes a completely different view of this technology in his work and believes that CMfg mainly stands out, for example, by the possibility of sharing production capabilities and resources through IoT or by connecting individual systems from different locations through an internet network through which they can help each other.

Augmented reality (AR) - is based on two basic building blocks. One is people (the workforce) and the other is the digital world/virtual reality. Thanks to this technology, it is possible to create so-called "super operators" in practice, which are characterized by the minimization of human errors, thanks to the implementation of digital technologies and visualization that provides maximum assistance during the performance of a given job (Forcina, 2021; Enrique, 2021). By Valentina (2021) can be identified the basic three specific subcategories, namely:

- Augmented and virtual reality
- Collaborative operator
- Healthy and super-strength operators

Augmented and virtual reality offers operators technology in the form of mobile phones, tablets, PC screens, headsets or virtual 3D glasses as part of the smart factory concept (Liagkou, 2021). In contrast, the second sub-category is devoted to the currently popularised form of interaction between an assistive robot (co-bot) and a human. Thus, in most cases, humans no longer have to perform e.g. highly repetitive tasks, work in non-ergonomic positions and/or handle heavy loads (Poor, 2019; Gao, 2020). On the other hand, this collaboration can initially be challenging for the person, as they need to be more cautious of individual movements within the workplace. Last are the so-called super-strength operators. This sub-category is characterized by the use of wearable technology that assists operators in performing activities that may cause damage to the human body. This usually involves some kind of physical activity in which the operator is subjected to excessive strain or is forced to perform a given movement repetitively (Kong, 2021; Pacifico, 2020). And these wearable devices are the ones that help operators in risky positions and at the same time some of them can monitor the progress of usage and optimize based on this data, e.g., execution time, job rotation or change of work activity/layout.

Autonomous robots - are considered as "signature" technology in Industry 4.0. Robots are now primarily associated with increasing productivity and quality in workplaces, while also saving energy and human health (Forcina, 2021; Gallo, 2021; Kmec 2018). In general, there are two basic types of robots available in robotics - autonomous robots and collaborative robots (called co-bots). Traditional autonomous robots always occupy a specific job position in manufacturing companies without any cooperation with an operator. Previously, the risk of injury was greater when entering this danger zone (Poor, 2019; Wegrzyn, 2020). Nowadays, even these heavy machines are equipped with sensors that can shut down the machine in the event of a breach of the work zone, knowing some damage. In practice, these robots are commonly used in activities that are very demanding and exhausting for humans e.g. today's car manufacturing would not do without robotic welders. In contrast, collaborative robots (co-bots) are set up to directly cooperate with an operator at a given workplace (Gao, 2020; Lima, 2019). In practice, they therefore perform activities that are primarily physically demanding for the operator, hence various heavy load handling or highly repetitive movements. In general, this technology allows the operator to focus more on more important elements such as quality or performance instead of focusing on how to manipulate heavy material (Atzeni, 2021).

3D printing or additive manufacturing - it integrates the basic triple combination (production process - computer - internet). The whole concept is based on working in a three-dimensional dimension, e.g. in CAD software or other 3D programs. Within this program, the user can design any shape according to the documentation, which is then printed layer by layer by a 3D printer (Chong, 2018; Prinsloo, 2019). In her article, the author (Lhotska, 2020) mentions that one of the biggest advantages of 3D printing in the context of low-volume manufacturing is the reduction of lead time and overall cost. The same idea is faced by (Dilberoglu, 2017) in his work, who sees the added value mainly in the level of flexibility that this technology offers. Compared to the traditional way of designing and manufacturing a new product, additive manufacturing can save a lot of time and costs, while producing what the customer just requires quickly, flexibly and in high quality.

Cyber security - it focuses on providing security for shared files, data and information that could be misused by third party users (cyber-attacks) (Khan, 2016; Fuertes, 2021). The author (Liagkou, 2021), sees three main differences between conventional Internet and CPS/IoT security systems, which are:

- A comprehensive way of implementing cybersecurity
- Cyber-attacks on physical systems
- Physical attacks on cyber systems

In contrast, the author (Prinsloo, 2019) in his work lists up to five basic types of cyber physical attacks. With some being able to cause a temporary total shutdown of the entire production (The Zotob Worm) or being able to tap into communication channels such as phone lines, cameras and network traffic to eavesdrop and obtain secret and valuable information.

1.2. Augmented reality as support for ergonomics in the workplace

As mentioned in the previous chapter, augmented reality (AR) is one of the nine key technologies characterizing the fourth industrial revolution. Terms of ergonomics and human-machine collaboration, this technology has a considerable potential, which can be mainly applied as a training tool in manufacturing companies (Enrique, 2021). Liagkou (2021) highlights the basic vision of Industry 4.0, which includes three key cases and one of them is the augmented operator. Whose potential lies in the continuous improvement of human qualities in the production process, provided the implementation of modern technologies (AR, VR or co-bot) that improve and accelerate the learning process while minimizing human errors and scrap (Mourtzis, 2018).

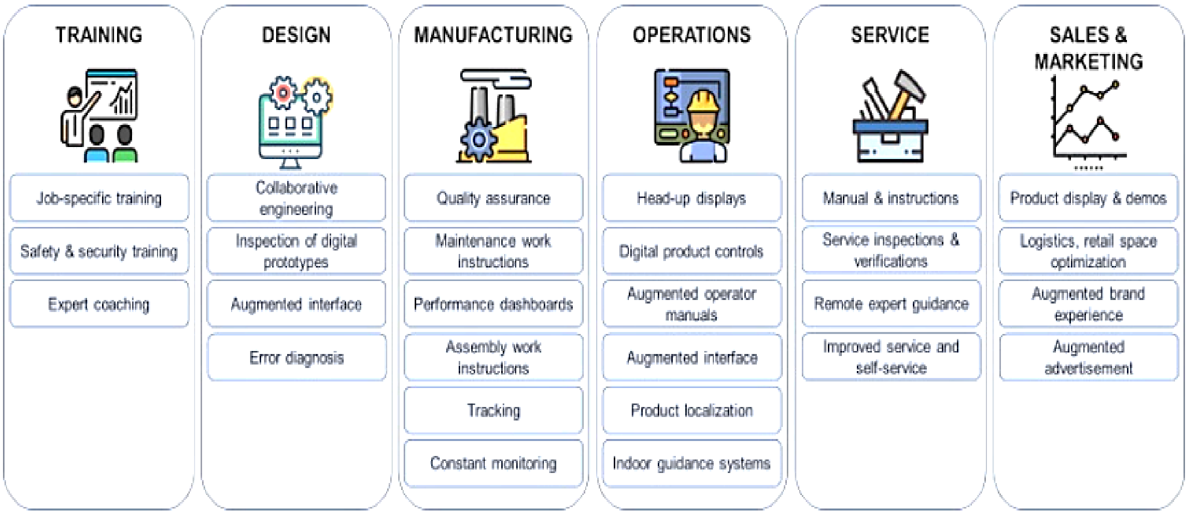


Figure 2. Six core areas for AR implementation (Alcacer, 2019).

But the question is: "In which areas can AR best be applied?". This question is best answered in the author's article (Alcacer, 2019), who identified six key areas where AR adds value. In Figure 2, each area can be seen.

Based on the results of the research of these two authors (Alcacer, 2019; Valentina, 2021), this article was created. It aims to identify pilot and specific technologies that can offer companies attractive optimization solutions. In Figure 3, a schematic of this article can be seen.

2. ERGONOMIC WORKPLACE ANALYSIS – BEFORE AUGMENTED REALITY IMPLEMENTATION

One example is in production maintenance. In his work, the author (Silva, 2019) used a tablet through which the operator scans a given panel or QR code, which then reveals potential malfunctions or warnings. In contrast, (Yew A.W.W, 2017) in his work uses a camera together with OCULUS glasses where the auxiliary steps are projected directly over real objects. Or (Masoni, 2017; Mourtzis, 2017) in his work deals with remote maintenance, where the operator takes a picture or scans the problem through the glasses and instructions are transmitted remotely on how to solve the situation. On the other hand, it is not only maintenance that has some potential for AR. For example, (Renner, 2017) in his work investigated how, through the glasses, participants place items into boxes in a virtual environment and how best to direct them so that the transfer is done correctly. While the author (Vidal-Balea, 2020) also considers glasses in her work. She relies on the attractive technology of Microsoft Hololens glasses to facilitate production and assembly activities by projecting VR assembly steps to operators.

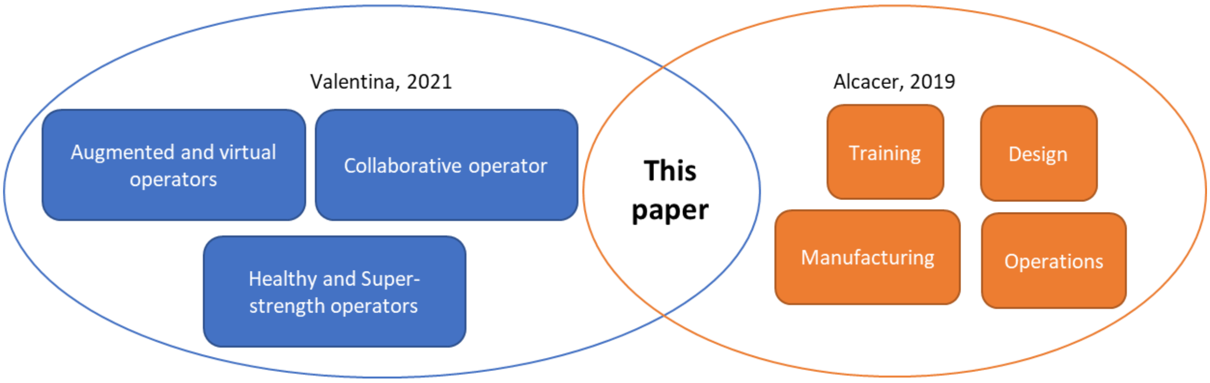


Figure 3. Concept of this article (own design).

It should be added, however, that AR is not only finding applications in manufacturing environments, but also in other sectors. In contrast, the author (Danielsson, 2018) has used AR technologies for accurate performance without any deviations during assembly activities. The author (Morgere, 2014) has used AR in shipping where with the help of interactive glasses and mobile application, it can easily identify the type and exact location of approaching objects. Or in the context of healthcare, AR is mainly applied as a means to train difficult and demanding operations where the precision and sequence of individual movements are crucial to success (Tagaytayan, 2018; Yoo, 2019; Uddin, 2021). Within this sub-category, I would like to highlight the work of (Aly, 2021) where AR was first used for vascular surgery, using a smartphone with a camera and gyroscopic sensors as a tool.

Thus, within this category, it can be concluded that AR is mostly used as a means to either train and learn complex surgeries or as an aid to remotely communicate with experts who can assist in identifying and fixing a given defect or problem.

2.1. Healthy and super-strength operators

This sub-category is divided into two parts. One deals with general health and the possibility of ensuring long-term stable performance (ergonomics). While the other one takes into account the use of technologies that directly increase the capacities of humans and allow them to perform very risky jobs in terms of their health (Valentina, 2021).

The first mentioned part is mainly captured by technologies that are more in the form of AR and in practice do not directly serve the operator, but the ergonomist or the person in charge, who has the task of identifying potential risks or threats in the workplace. Such an imaginary precursor of AR is the "Datalogger" by (Dombeková, 2018). This technology has five pressure sensors placed on the fingertips to identify the force exerted in % Fmax for the extensors/flexors of the operator based on the imaging. If the limit value is exceeded, measures must be set immediately to reduce the local muscle stress (LSZ), which mainly arises from the high repetitiveness of the same movements. A similar approach has been applied by (Borik, 2019) in the development of a smart glove that aims to measure grip forces and assess the risks of excessive physical stress.

In contrast, the first realistic VR models can be seen in the works of (Gašová, 2017; Beuss, 2019; Vosniakos, 2017). In her work, Gašová (2017) focuses on an ergonomic application through which a given workplace can be scanned and in VR the different areas of movement and reach are projected on the workplace. Based on this comparison of reality with VR, the workplace can be adjusted according to the needs of the employee. Beuss (2019), on the other hand, used a system of cameras and markers that record the entire movement sequence of the operator in VR. Subsequently, the ergonomist/responsible worker in the VR (from a third-person perspective) highlights inappropriate working positions that must be eliminated. Vosniakos (2017) applied a similar principle to (Beuss, 2019), except that a reality-based virtual work sequence was created for 9 unskilled operators who were asked to evaluate the total physical stress in each key body part after VR. For these examples, a very popular motion capture technology called MOCAP was applied, which scans and records the individual movements of the operators through a digital human body via cameras and sensors. The authors (Du and Duffy, 2007) created the very first digital human body model for possible analysis. On the other hand, 10 years ago (Longo and Monteil, 2011) there were already other technologies such as Siemens Tecnomatix Jack®, Dassault Delmia Human® and RAMSIS® that could simulate humans during work activities. Motion capture in its best form should work in such a way that it can transfer both the human and the workplace in which it moves to VR, only in this way a high degree of synergy can be achieved. Even the authors (Nikolakis and Alexopoulos, 2019) confirm this in their work, stating that simulation versus MOCAP technologies can provide inaccurate results because they do not sufficiently replicate the freedom and naturalness of human movements. Currently, the state-of-the-art is the so-called marker less optical MOCAP, which uses a system of cameras and special software that, after inputting basic information about the operator (height, weight, distribution of body parts), can identify each key joint even without visible markers (Puthenveetil, 2015; Ferrari E. et al., 2018). So far, the best possible prototype of marker-free optical MOCAP is the MAS (Motion-Analysis-system) by the author (Bortolini M. et al., 2020).

In last year's there occurs a potential of human body ergonomic improves in the form of exoskeletons, this support and eliminate physical stress for operators in unnatural positions (Kong, 2021; De Looze, 2015; Constantinescu, 2016). Exoskeletons are used by human physically demanding operations. His main purpose is to eliminate manually burden by human (Yong Xu, 2019; Sylla, 2014).

2.2. Combination of ergonomics and AR

The technological changes that are coming to industrial companies with the concept of Industry 4.0 have also significantly affected the technology of ergonomics. Above all, the active implementation of technologies such as mobile applications, tablet integrated applications, data gathering, real time screening of machine and people brought new way of thinking about structure and content of ergonomic workplace organisation and management. Advanced ergonomic tools based on Industry 4.0 concept are a new direction in ergonomics that concentrates the effort on the development of healthy conditions at work for production workplaces.

Based on the above research, a scheme for linking ergonomics and augmented reality was proposed Figure 4. This diagram shows how a suitable ergonomic workplace could be set up in the near future. This scheme is based on three basic pillars or perspectives on how the link between ergonomics and augmented reality can be applied. The mentioned scheme is technologically supported by 3D scanning and workplace modelling in Technomatix Jack in combination with augmented reality. In this context, the quality of inputs, which is based on traditional ergonomics procedures, is important. Based on the inputs, we detect the required input variables for tools integrated in augmented reality and simulate variant solutions. The effect of augmented reality therefore consists in the correct combination of inputs and criteria for assessing simulated variants of the ergonomic solution of the workplace. The results of several simulation solutions showed us that while the simulation model is acceptable in AR, it is often unacceptable in its entirety for the ergonomic setting of a person’s working position or an ergonomic workplace.

From this reason, we decided to support the mentioned schematic model with virtual reality. We started from the knowledge that AR maps the real world and VR a fictional world. AR technologies are integrated in a smartphone (screening, data collection, etc.) and VR require specialized software. Experience from simulations showed that while it was possible to desing an “ideal” ergonomic workplace in a VR fictitious world, by simulating in AR we revealed several boundaries, that limited the “optimality” of the proposed ergonomic workplace.

Based on this analysis, which would be performed by the user from multiple perspectives, the valuable data would be sent to simulation software, which would then suggest the ideal workplace condition for the 95th percentile of employees. The author Vignais (2013) has already reported something similar in his article where he paired augmented reality, IMUs sensors and the RULA method, where during a dangerous movement the operator was informed through glasses which part of his body was overloaded.

The second pillar is focusing on the modern concept of ergonomics and AR in real scenarios where operators already have AR technology for working purposes. If they were equipped with AR goggles to instruct them on how to perform their work, software could be embedded in the background of these goggles to assess the operator's working positions. If a bottleneck was detected, this data would be provided to the continuous improvement unit where a corrective solution would be implemented.

The last pillar is mainly devoted to the design part, which is mainly related to the development of a new product (Wang, 2013). Various automated approaches are currently being used which, on the one hand, can check the connection and interaction of the technology with the operator, but there is still a lack of insight into ergonomics in most cases. This is also why technologies such as simulations should be applied in the design process, which can project the individual operator activities in a virtual environment. Thus, in conjunction with AR, once a simulation is created, it should be possible to link a real operator to a task in VR, where the bottlenecks and risks related to overexertion and non-physiological positions of operators at work should be revealed based on the completed task.

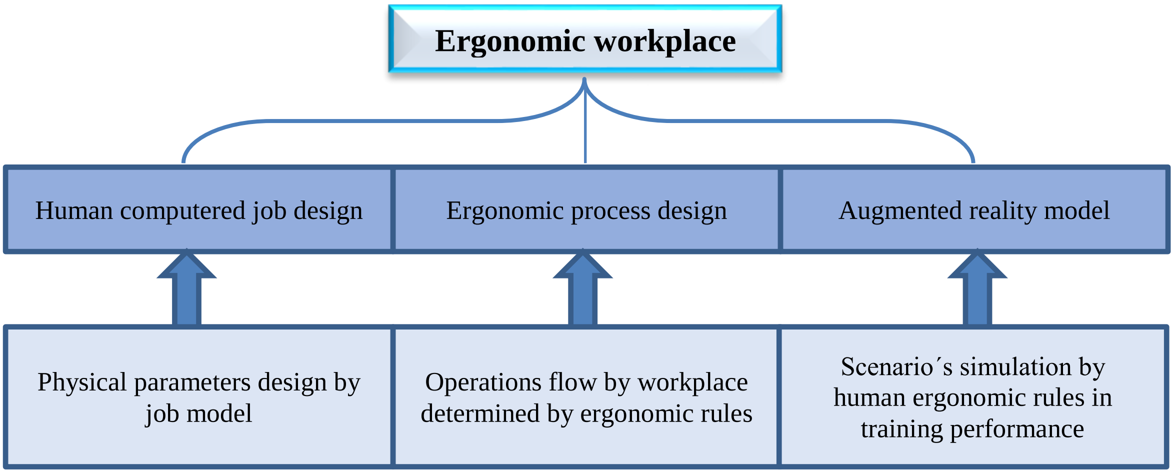


Figure 4. Combination of ergonomics and AR in 3 main pillars (own processing).

3. CASE STUDY

The data analysed in the following case study express the complexity of the traditional ergonomics procedure. Their transformation into VR consisted in qualifying the eligibility of the given factor for use in ergonomic analysis. Subsequently, they were used for AR in the format of confrontational parameters (defining the interval of permissible values of the selected ergonomic parameter) in combination with the screening of a real workplace. The carpal tunnel was chosen as a type representative for data analysis. The reason for this was the fact that, from the point of view of workplace ergonomics, it is one of the most frequently occurring problem parameters. In connection with the other data presented in the case study, this is a relevant approach to a comprehensive data analysis of workplace ergonomics.

Based on the above-mentioned literature search, this case study was created to examine the incidence of occupational disease hereafter referred to as OCD in the Czech Republic from 2002 - 2020. Figure 4 below shows the individual steps of the case study data processing.

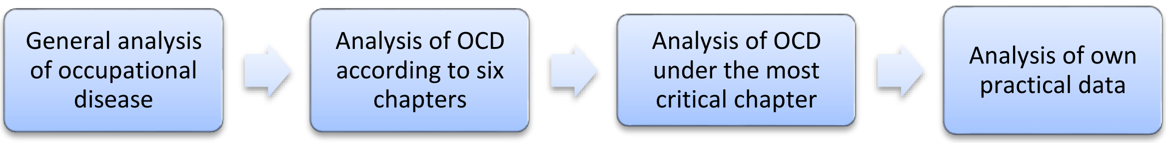
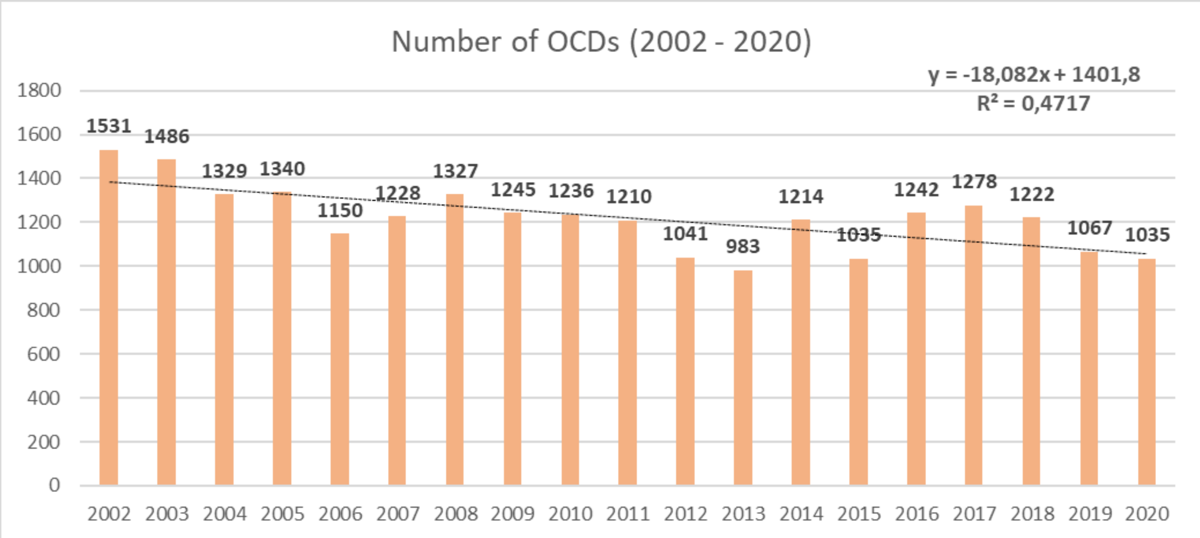


Figure 5. Individual steps of the case study (own design).

3.1. OCD in years 2002 – 2020

In Table 1, the total number of reported occupational diseases in each year can be seen. A linear trend has been plotted in the graph, which shows us a decreasing trend. This decline over the years is mainly due to the greater interest in ergonomics and technology, which is constantly battling inadequate working conditions in workplaces.

Table 1. Number of OCDs between 2002 and 2020 (own design).



The coefficient of determination R2 indicates the percentage of explained variability, where approximately 47% of the variability in the time series is captured by the model and 53% is no longer accounted for, so it will change randomly. When the other trends were tested in MS Excel, the two trends (logarithmic and power series) proved to be the best variation, with both showing an approximate variability of 61% and hence showing the highest percentage of variability in the time series.

3.2. OCD within chapters 2002 – 2020

For a more detailed analysis of the individual occupational diseases, a selective analysis of the OCDs in the above years was performed according to the predefined chapters/criteria. A total of six basic chapters are defined. These chapters are:

- Chapter I - OCD caused by chemical factors
- Chapter II - OCD caused by physical factors
- Chapter III - Respiratory, pulmonary, pleural and peritoneal diseases (cancer, asthma, pneumoconiosis)
- Chapter IV - Cutaneous OCD
- Chapter V - Communicable and parasitic diseases
- Chapter VI - OCD caused by other factors

In Table 4 below, a graphical representation of the overall incidence in each chapter across years can be seen. Through this analysis, it was found that **Chapter II - Occupational**

Diseases caused by Physical Factors had the highest incidence of all the periods studied. The total of all years represented a value of 10985 cases. Chapters III, V and IV were ranked 2nd-4th in order, with an incidence 2.5 to 3 times lower than Chapter II. Therefore, Chapter II will be examined in more detail to support the results of the literature search.

The descriptive statistics further revealed that during the years under review, Chapter II. Chapter, the annual average of those who fell ill was determined to be **578 people**. The variance and standard deviation were also determined. For this sample of data, the variance was **7484, 58** and by subsequent subtraction, a relatively high standard deviation was obtained with a value of **86.5 sick people**. According to theory, subtracting or adding this value of 86.5 from 578 gives a range that accounts for **approximately 68% of cases**. When compared with the median value, it was found that the arithmetic mean is not directly in the middle of all the observed values, but skews towards a higher value. The median value of this sample is around 546, thus **about 32 fewer sick people than the mean value**. On closer examination of the individual frequencies in the years of Chapter II, it can be seen that the whole pattern was mainly influenced by atypically strong years, resulting in an upward shift of the mean.

Based on this result, a more detailed statistical analysis was developed using the G*power statistics program and is presented in the next subsection.

3.3. Analysis of OCD caused by physical factors

In the previous subchapter, it was revealed that between 2002 and 2020, OCD caused by physical factors are the most critical. The aim of this subchapter is to specify as much as possible the most common OCDs (under Chapter II), which should be taken into account mainly by preventive measures. Within Chapter II, there are four main groups of diseases:

- Noise-induced perceptual cochlear hearing loss
- Vibration-induced hearing loss
- Diseases from LTEUS (long-term excessive unilateral stress)
- Other OCDs

The overall frequency of each of the Chapter II diseases in the years under review can be seen in Figure 8 below. According to the graphical representation of the results, it can be concluded that the most serious group of occupational diseases are diseases caused by long-term excessive one-sided load, so called DNJZ. Carpal tunnel syndrome is considered to be the best known and most widespread disease in this area.

An Excel spreadsheet (Table 2) was also created that mapped the incidence of carpal tunnel from DNJZ proportionally in males and females for the years 2010 to 2020. For the purposes of this article and timeliness, only the last 10 years were selected. In this analysis, minimum, maximum and median values were determined in two domains: age and exposure.

Table 2. Median, Min and Max in each year (own design).

Carpal tunnel (from overloading) development in years (2010 - 2020)								
Year	Men	Women	Age (in years)			Exposure (in years)		
			Median	Min	Max	Median	Min	Max
2010	77	153	51	22	63	5	0,09	42
2011	84	151	47	20	60	4,3	0,12	35
2012	76	113	48	23	61	6	0,15	39
2013	54	122	47	22	61	5	0,1	40,4
2014	67	135	47	22	62	5	0,03	39
2015	75	166	49	21	64	6,4	0,01	46
2016	86	181	48	19	65	4,7	0,17	43
2017	88	242	48	20	64	5,4	0,01	38
2018	87	198	49	21	63	3,16	0,11	44
2019	61	131	48	30	62	4,8	0,08	42
2020	51	124	49	23	66	4,7	0,03	43
Total/average:	**806**	**1716**	**48**	**22**	**63**	**5**	**0**	**41**

At the same time, based on the author's curiosity, the mutability of the data sample was calculated in Excel. According to the theory, the mutability ranges from 0 - 1, where based on our result determines how many % of all possible pairs can be randomly selected to obtain pairs of opposite values. Within this sample, the comparison is between a male and a female. In Table 3, one can see the result of this test, which indicates that based on this sample, if all possible pairs were randomly selected, approximately 44% would be with opposite sexes (male/female), while the remaining 56% would face two possible alternatives (male/male or female/female).

Table 3. Mutability of the sample (own design).

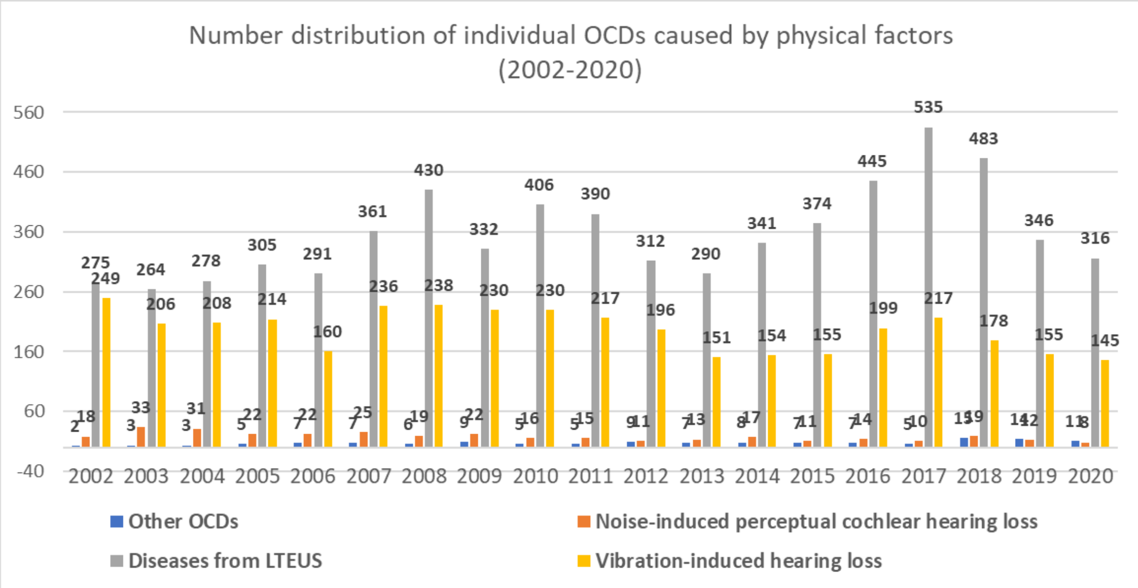
Popis	abosult frequency	relative frequency	ni2		
Man	806	32%	649636	Mutability=	**0,44**
Woman	1716	68%	2944656		
Total	2522	100%	3594292		

Subsequently, a force analysis was prepared in G*power. The following parameters were set in the program: observations within both ends (2 tails), effect size of 0.2, long-term error rate is at 0.05, on the other hand, the long-term power was worked with a value of 0.95. The allocation ratio was set to 2 because we know from Figure 6 and 7 that we do not have two groups of equal sizes.

Based on the input, the G*power program found that if I want to identify an effect size at a Cohen's value of 0.2 with 95% power (alpha = 0.05, two-tailed) then I need **488 respondents** (diseased) in one group for this research, and **976 (n = 1464)** in the other group for independent t-tests.

After generating a sample power analysis, a sensitivity analysis was further applied, which claims that when testing independent samples with 806 diseased in one group and 1716 diseased in the other group (n = 2522), the test is sensitive to the effect of Cohen's d = 0.15 with 95% power (alpha = 0.05, two tailed). This result can be interpreted as follows. This data sample will not be able to reliably detect effects smaller than Cohen's d = 0.15.

Table 4. Numerical distribution by disease (own design).



3.4. Statistical analysis of the collected data

Based on the above results, I was able to apply my research in practice. From 2019 to 2021, I collected data across manufacturing companies across the country. Within this time period, I subjected approximately 93 workplaces to a thorough screening. Individual workplaces were selected based on criteria I set, the main ones being:

- The workplace or work can be classified under Chapter II, specifically, diseases from LTEUS
- The experience curve of the individuals screened had to be greater than 3 months
- The selected individuals did not have any permanent disease and also did not get injured during the screening process

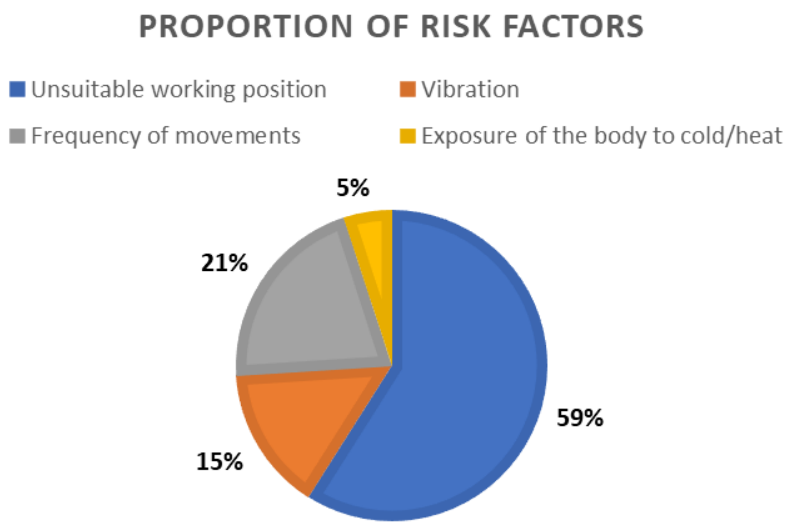


Figure 6. Proportion of risk factors in % (own design).

At the end of the research, about 5 to 10 different risk factors were identified. Of these, the highest frequency was for: unsuitable working position, vibration, frequency of movement and exposure of the body to cold/heat. In Figure 5 below, the % expression of each risk factor can be seen. This data was further applied in hypothesis testing.

3.4.1. Chi-square test on the influence of cofactors on carpal tunnel formation

The core goal of this test was to determine the dependence of the development of carpal tunnel disease from congestion if it is caused by at least one of four possible risk factors. Hypotheses were defined as follows:

H0: There is no relationship between carpal tunnel disease from congestion and the presence of risk factors.

H1: Carpal tunnel from congestion and risk factors are interdependent

The following Excel spreadsheets were used for this test. First, a contingency table was created that contained the individual factors and their frequencies

Table 5. Observed frequencies (own design).

Observed frequencies: nij					
	Unsuitable working position	Vibration	Frequency of movements	Exposure of the body to cold/heat	**Total:**
YES	32	21	18	7	78
NO	7	5	2	1	15
Total:	39	26	20	8	**93**

Based on the frequencies, theoretical frequencies were calculated + a test criterion was

Table 6. Theoretical frequencies (own design).

Theoretical frequencies: eij				
	Unsuitable working position	Vibration	Frequency of movements	Exposure of the body to cold/heat
YES	32,70967742	21,80645161	16,77419355	6,709677419
NO	6,290322581	4,193548387	3,225806452	1,290322581

Table 7. Test criterion (own design).

Test criterion: Kij				
	Unsuitable working position	Vibration	Frequency of movements	Exposure of the body to cold/heat
YES	0,01539734	0,029824394	0,089578164	0,012562035
NO	0,08006617	0,155086849	0,465806452	0,065322581

also established

With all these data, a chi-square test was calculated with a p-value of 0.82. **Thus, the H0 hypothesis cannot be rejected at the 5% significance level.**

3.4.2. ANOVA test

The last test in this research is the ANOVA test. Here, the average frequency of movements for surgery at workplaces where this particular risk factor was identified will be tested against those workplaces where it was not present. The hypotheses for this test were set as follows:

H0: The effect of the risk factor in relation to the operation performed is insignificant.

Table 8. Frequency at individual workplaces (own design).

Workplace A	Workplace B	Workplace C	$(\bar{a} - a)2$	$(\bar{b} - b)2$	$(\bar{c} - c)2$
249	254	250	0,64	8,41	0,49
249	249	247	0,64	4,41	5,29
247	249	251	7,84	4,41	2,89
250	250	251	0,04	1,21	2,89
251	253	248	1,44	3,61	1,69
252	252	250	4,84	0,81	0,49
249	250	249	0,64	1,21	0,09
249	250	248	0,64	1,21	1,69
252	251	249	4,84	0,01	0,09
250	253	250	0,04	3,61	0,49
249,8	251,1	249,3	21,6	28,9	16,1

H1: The effect of the risk factor in relation to the operation performed is significant.

For this test, a table was created that contained the individual frequencies for 3 different workplaces when 10 workers were imaged sequentially (Table 8).

First, the arithmetic mean (green boxes) was calculated for each site. This value was then used to calculate the individual 'squares' (yellow box).

In the next Table 9, we can see the values of the individual statistical parameters, which I describe in detail below.

Table 9. Statistical parameters (own design).

Source	DF	SS	MS	F	P-value
Factor	2	17,26667	8,633333	3,5	0,045
Error	27	66,6	2,466667		
Total	29	83,86667			

The DF value represents the degrees of freedom. In this particular case, I had a total of 30 values measured (10 workers x 3 workplaces). According to the formula, the value is set to 29. In terms of the freedom factors, I had 3 workplaces (A, B, C), according to formula 2. With the difference of the total DF and the DF factor, I get a degree of freedom called noise 27.

I obtain the value of the mean square as follows. I get the value 83.8 from the arithmetic mean of all 30 frequencies according to the formula (mean of all frequencies - individual frequencies) ^2. In contrast, I obtain the value of 66.6 by summing all the yellow values for Figure 13. The subsequent value of 17.2 is obtained by the difference of these two values.

I obtain the MS value for both factor and noise by dividing the corresponding SS by the DF value in that row, for example, 17.2 / 2 = 8.6333. The subsequent F value is the value of the Fisher distribution, which I obtained by dividing the MS factor / MS noise values.

However, the most important value for the whole test is the p-value level, which was obtained through the FDIST function, which needs the values of F, DF factor and DF noise for its calculation.

The resulting p-value took the value of 0.045, i.e. 4.5%. **Because of this value, we must reject hypothesis H0 and accept hypothesis H1.**

DISCUSSION AND FUTURE WORK

Ergonomics is an important component of process management in industrial companies. The mentioned article describes the issue of the procedural approach in the field of ergonomics using the principles of traditional ergonomics procedure and data analytics for VR/AR. The authors are based on a literature search that presents key theoretical knowledge from the field of Industry 4.0, points to technological trends in the field that can be used for the implementation of selected digitization tools in industrial companies as well. In this section, elements are presented that are already used in industrial companies and where implementation efforts can be mapped in order to obtain important insights for the detailed steps of digitization also in the field of ergonomics. An essential moment is the understanding of the process procedure, which is a necessary prerequisite for the connection of ergonomics and augmented reality. In the end, a case study is presented, it deals with occupational diseases, further referred to as OCD. The results of the mentioned case study were monitored in the Czech Republic in the years 2002 - 2020. The result of new digitally supported process procedures in the field of ergonomics were presented as a core content of data analytics for VR/AR digitized support of ergonomic design. For the above reason, the field of augmented reality also has a justified use, which opens up a number of possibilities for flexible and optimal adjustment of the ergonomic load of a person. In the coming years, our research efforts will also be focused on more detailed scientific research into the working conditions of workers in industrial production, the optimal setting of workflow, production layout and other key parameters of the production system. This is due to the fact that the combination of digital tools, the integration of robots and cobots in the workplace has brought new challenges to the field of workplace ergonomics. In many workplaces, robotic or digitized technology sets the process pace, and humans are de facto controlled. He is no longer in a position where he sets the pace. Therefore, it is necessary to study the impact of digital technologies on the ergonomics of work to the maximum extent in the next period and subsequently create methods for optimal setting and human involvement in productive activities at the workplace.

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