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From the Editors

Editorial Statement: War in Ukraine

Late February of this year, the peace that has reigned in Europe for almost 20 years was shattered by an unprovoked attack on a sovereign state. In the aftermath, the democratic countries of Europe and beyond have united in their efforts to aid Ukraine, which continues to fight for its independence even now.

Common European values are built around the protection of human rights, the same rights that are threatened by the senseless violence and indiscriminatory tactics of the Russian troops invading foreign territory. Both governments and the popular opinion have condemned the unapologetic violation of the international law and expressed sympathy for the plight of Ukrainians.

Our editorial team could do no less. We denounce bloodshed in any form, but especially when its victims are the innocent women and children who have no means of defending themselves. We believe in the rule of law and the principles of common decency. No war is ever fought without casualties, but civilian losses cannot be justified in this day and age as mere collateral damage for the supposed righteous cause. Not with the capabilities of the modern warfare, not with the truth so clearly shining through.

We stand with Ukraine. We admire and commend the Ukrainian people. We pledge our support to their fight and their continued resistance. Millions of refugees who have now settled in Europe and tens of millions who remain to meet the challenge need help, so we must ensure they receive it.

Academia and the world of science and research have long since transcended borders, but in times like these even theorists cannot stand aside. We have the privilege of having published many papers by distinguished Ukrainian authors and we are eager to review new submissions from Ukrainian contributors.

Stay strong, our Ukrainian friends! Stand firm and know you have steadfast backup at your back. Glory to Ukraine and glory to its heroes!

Editors

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From the Editors-in-Chief

THE VALUE OF SUPERDIVERSE HUMAN-TECHNOLOGY ENTANGLEMENTS

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Abstract: *Human-technology relations are time and place related processes. Today, it is very common to describe human-technology interaction by stating that technology is ubiquitous and permeating all aspects of our everyday lives. This is often compounded by the fact that technological development has been rapid, and it seems to be accelerating. This speed makes the understanding the effects that technology has on us and our lives challenging or even difficult to realise. These kinds of notions have been repeated for decades already. The point here is not to criticize other scholars, but to argue that to reveal the value of quotidian human-technology entanglements we need to focus on the most mundane parts of our lives, scrutinizing something we do not necessary recall nor take notice of. This has been labelled as the "secret world of doing nothing" by ethnologists Billy Ehn and Orvar Löfgeren (2010) to describe the most mundane activities of our everyday lives.*

Keywords: *technological development, technology, human-technology, technoculture.*

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Sifting Understandings of Technology and the Digital Everyday

Looking back, it is easy to see how the developments in technology have shaped researchers' understanding and interests. In the late 1980's and early 90's researchers understood new technologies, the internet, and developing digital world as a new realm, new entity where different kinds of cultures could evolve. For example, in 1991 Constance Penley and Andrew Ross wrote about *technoculture*, and the need to understand both pros and cons of new technologies. They were concerned about the spread of Western technologies and how this might impact other cultures. They argued that technologies were far from neutral, "like all technologies, they are ultimately developed in the interests of industrial and corporate profits and seldom in the name of greater community participation or creative autonomy" (Penley & Ross 1991, xii). Some scholars criticized the concept of technoculture as being connected to technological determinism, but Penley and Ross have stressed the importance of cultural negotiations before adopting new technologies to limit the westernisation that they might bring. They also have raised the importance of bringing forth different, parallel narratives that can exist simultaneously.

A few years later, anthropologist Arturo Escobar and his colleagues wrote about *Cyberia*, a new cultural order, which described the social changes brought about by computers and information and biological technologies (Escobar 1994). Cyberia was seen as a concrete space, clearly distinct from everyday life. From the mid-2000s onwards, online research focused on Web 2.0 thinking, the backbone of which was formed by social media and various applications such as Facebook (Miller 2011) or social games such as Second Life (Boellstorff 2008) and their cultural reviews (Caliandro 2018). The concept of Cyberia seems to be constantly evolving, in part due to the development of new platforms such as the metaverse. In 2010s, phenomena such as datafication, big data, and algorithms have become the subject of research (see, e.g., van Dijck 2014; Lehtiniemi and Ruckenstein 2019; Lugosi & Quinton 2018). Researchers have also discussed widely issues of inequalities, power relations, artificial intelligence, and ethical aspects of technology in the online world (e.g., Helsper 2021; Hine 2015; Richardson 2015). These discussions indicate how important understanding and conceptualising time, and temporalities is.

Human-Material Entanglements

Human-technology relations are also part of our material relations, and this materiality is closely intertwined with the social and cultural. Digital technologies have also created a form of materiality, which is not so much 'im/material' but rather "in-material"', and we are not always even aware of all the forms of materialities that exist (van den Boomen et al. 2009, 9). For example, software is a kind of materiality incorporated in a physical device that we do not often consider material, because materiality is usually connected to tangible things.

These material relations are also connected to a rather controversial question concerning agency: who possesses the ability to act? In her research, Kristiina Korjonen-Kuusipuro studied both the digital everyday of older adults and young people and learned that the "new digital normal" means different things for different people. On the one hand, older adults are often seen to be at risk of marginalization because of digitalization, and they are encouraged, sometimes even obliged to learn how to use, and use technological devices and services. On the other hand, younger people are still often referred as digital natives, very competent users of all digital services and devices. With youth, the focus of discourses is often on the time spent using digital devices (so-called screen time), and the level of addiction they may have developed when gaming or just watching YouTube, for example.

Future Avenues for Understanding Superdiversity

We often expect technology to be something magical and we sometimes even believe in “a digital promised land”. However, it has become clear that technology does not bring equal opportunities and possibilities to all (for example, Helsper 2021). When doing research on quotidian human-technology relations, we are faced with *superdiversity*, the diversification of diversity (Vertovec 2007). The concept of superdiversity is usually used in migration or sociolinguistic contexts (for example Blommaert 2013), but Varis and Wang (2011) have used the concept to describe the diversity of the internet as a space where “the diversity is constrained by a complex of normative struggles, as new forms of meaning-making are accompanied with new systems of normativity”. The complexity of human-technology entanglements is overwhelming, and the challenge is how to capture and conceptualize it adequately. From the human viewpoint *techno-anthropology* (e.g., Ruckenstein 2015) might be one solution. On the other hand, from the technological viewpoint human-computer interaction and user experience studies support the discovery of useable and intuitive human technology relations. Together these viewpoints enhance the understanding of human-technology relations and may reveal the hidden patterns people and technologies co-construct in their daily lives.

Even though there are different ways of looking at human-technology relations, what is usually neglected are the various ways how cultural values, norms, practices, and meanings influence these relations. Culture means also sharing, and this sharing may arise from the need of reciprocity, an asymmetry between informal and formal knowledge, or a need to act through local communities, rather than individuals. Understanding differences among communities needs an empathetic understanding, because it is only through empathy that different kinds of experiences and voices can be heard. There is also knowledge that is not or cannot be expressed in a narrative form, with words. This knowledge includes for example bodily activities, feelings, emotions, and affects. These are challenging, but not impossible to research. For example, *sensory ethnography* developed by Sarah Pink (2009) offers one possible means of considering our perceptions, place relations, knowing, memory and imagination. It is also possible to combine sensory ethnography with participatory methods for more collaborative knowledge-making in which discursive, embodied and non-human perspectives that *come into being* in multiple intra-actions (for more about intra-actions, see Barad 2007; about collaborative knowledge-making for example Suopajärvi 2017).

Interestingly, technological imagination, or even daydreaming can have the power to allow people to explore possible futures, the abnormal, and even crazy ideas (see also Ehn & Löfgren 2010; Halse 2013), but also allow them to explore their everyday life as a meaningful subject for research. Sometimes people involved in research projects are skeptical about the significance of their mundane experiences. Therefore, we should also develop ways how we in concretely show people in what ways their experiential knowledge has been used, for example in co-design processes. Ethical issues will need to be carefully considered within these processes. For example, those who plan technical solutions for older adults often justify them by saying that it may reduce the need to move around the house or reduce their need to visit local services in person, for example. However, this kind of movement could be of vital importance to support the older people's physical and mental activity. Furthermore, data recorded when creating or profiling technology for society should also be handled with caution. Very often they hide traits, perhaps unintentionally, that we seemingly do not notice, and in the wrong hands can be used to build discriminatory mechanisms.

Despite all these technological, social and cultural developments and changes, we still need to stress that technologies are far from neutral. They are results of social processes and include multiple power relations (also Penley and Ross 1991). From the social and cultural point of view, human-technology relations are also about belonging to society. The sense of belonging is central to human experience; it is a relational and dynamic process of emotional attachment that is under continuous (re)negotiation and requires contextualized definitions. Thus, scrutinizing both the human and the technological is of vital importance for equality of digital societies.

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FACTORS INFLUENCING THE INTENTION TO USE ASSISTIVE TECHNOLOGIES BY OLDER ADULTS

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Abstract: *Society is ageing at an unprecedented pace worldwide creating implications for the health and social care. Gerontechnology has been recognized as a solution that increases and supports the independency and well-being of older adults at home. This article aims to identify the most critical success factors effecting the adoption of an assistive gerontechnology by older adults in Poland. The object of the authors' interest was Rudy robot, an AI-enabled mobile solution helping users remain physically healthy, mentally sharp, and socially connected. The data was collected among Polish citizens using the CATI technique between November and December 2020. The number of returned questionnaires amounted to 824. The authors used Generalized Least Squares (GLS) of Structural Equation Modelling (GLS-SEM) to verify the hypotheses. The obtained results confirmed statistically significant relationships between the variables of perceived usefulness of Rudy robot and attitude reflecting the willingness to use this technology, as well as between perceived ease of use and perceived usefulness of robot. However, relationship between perceived ease of use and inclination to use this technology in the future was not statistically significant. The conducted research confirmed that the functionality of the analysed Rudy robot for older-adult care positively influences their intension to use it in the future for their own needs or family members. The obtained results confirmed usefulness of robots as assistive technology helping older adults.*

Keywords: *assistive technologies, gerontechnology, technology acceptance model, robot, older adults.*

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INTRODUCTION

As the World Health Organization projects, global population will become a super-aged society by 2050. Over the next decades, the number of people aged 65 years or over globally is predicted to increase from around 1 billion in 2021 to 1.4 billion in 2030 up to 2.1 billion in 2050 (World Health Organization, 2021a). In 2021 the proportion of older people accounted to about 13.5% of general population, however 1 in 6 persons will be 60 years of age or older by 2030 (World Health Organization, 2021b). The demographic changes have diverse implications for society and economy worldwide. Society is ageing at an unprecedented pace worldwide, which will accelerate in the future, particularly in developing countries of Eastern and South-Eastern Asia, Latin America and the Caribbean (United Nation, 2019). However, nowadays the process of population ageing is most advanced in the European Union. Moreover, the number of residents on the Old Continent is predicted to decline rapidly over the coming years. Europeans live longer than ever before and the age structure of society is rapidly changing, with proportion of people of working age shrinking and the number of older people expanding (Eurostat, 2020). The demographic old-age dependency ratio between older people and those of working-age is projected to grow significantly in the European Union in the coming decades. The proportion of older persons in the EU (aged 65 and over) is estimated to reach 25% of total population by 2030 and 30% by 2070, while the share of working-age persons (between the ages of 20 and 64) will reduce from 61% in 2030 to 56% in 2070. This means a shift from less than four working-age people for every person over 65 in 2010 to below two in 2070 (European Commission, 2021). Considering economic effects, more will be spent on pensions while the share of taxes will decrease. Population ageing has implications for public health and social care, as more people will have diseases related to the old age such as dementia, which is considered one of the greatest challenges for health and social care in the 21st century. Nowadays 50 million people worldwide suffer from dementia, but this number is predicted to triple by 2050 (European Parliament Technology Assessment, 2019). According to World Health Organization, at least 142 million older persons worldwide meaning 14% of world population, are unable to meet their basic need, while as much as one third of people over 65 need assistance with at least one activity of daily living for example eating, bathing, dressing (World Health Organization, 2021b). The number of people requiring extended care due to disability or functional limitation is likely to increase worldwide. In consequence, the lack of caregivers in social care and shortage of nursing staff leads to a greater responsibility falling on informal carers, who frequently leave the jobs to take care of their family members (European Parliament Technology Assessment, 2019). Along with ageing process, seniors have to face limitation of their movement and mobility. As people get older, rising health problems may lead to shrinking of their activity space and reduced participation in physical activity. As homes, everyday objects and communities, which are not originally designed considering seniors' need, become rather obstacles to movement, safety, independence and socializing (Tsai et al., 2015). Among emotional problems, the older people usually have to face ageism and outdated social norms, which result in their isolation and marginalization in both rural and urban communities (Grenade & Boldy, 2008; World Health Organization, 2021c). Even worse, last year was extremely difficult for elderly people as they had further reduced access to health care and social support due to pandemic caused by COVID-19. Moreover, permanent restrictions have not only affected older people's daily routines, but also their ability to stay socially connected and how they are perceived. Older people facing changing regulations, are obliged to spend more time at home, which result in the lack of physical contact with other family members, friends and colleagues, temporary cessation of employment and other activities and finally increasing anxiety and fear of illness and death – their own and others. In result, COVID-19 has further exacerbated the problem of loneliness and social exclusion of older adults (Brooke & Jackson, 2020; Richardson et al., 2020).

Despite many challenges considering ageing population, older people can contribute into community bringing their long term experiences, knowledge and time. Staying fit and healthy is an important factor prolonging work participation and ensuring good life quality of seniors. New and creative solutions or technologies dedicated for older adults should be introduced not only to use their wisdom but also to provide opportunities for lifelong learning and meaningful engagement across the lifespan (World Health Organization, 2021b). One of the solutions enabling older people independent living are gerontechnologies, which aim to improve the life of ageing people and to facilitate their participation as full citizens in their own society. Various technologies have been researched in the context of elderly use, among others: Virtual Reality (Syed-Abdul et. al., 2019); robots (Broekens, Heerink & Rosendal, 2009; Chu et al., 2019; Heerink, Kröse, Evers & Wielinga, 2010); healthcare wearable devices (Wang, Tao, Yu & Qu, 2020; Li, Ma, Chan & Man, 2019); m-health technologies (Cajita, Hodgson, Lam, Yoo & Han, 2018); Internet of things (Maskeliūnas, Damaševičius & Segal, 2019); smart home (Arthanat, Wilcox & Macuch, 2019); intelligent wireless sensor system (IWSS) (Cohen, Kampel & Verloo, 2016), ICT technologies (Ha & Park, 2020); assistive applications on smartphones (Petrovčič, Peek & Dolničar, 2019); intelligent wireless sensor system (IWSS) (Cohen, Kampel & Verloo, 2016).

This article aims to identify the most critical success factors that can explain the adoption of a gerontechnology by older adults in Poland on example of RUDY robot. The paper is structured as follows: first, the literature review on gerontechnology and its application for the purpose of older adults care was conducted. Based on the literature review theoretical model and hypotheses are presented. After, the theoretical part of the article, research method and analysis are presented. Next, the findings are discussed. Final conclusions, practical implications, limitations and areas of opportunities of future research are outlined in the last part.

LITERATURE REVIEW

The discipline of gerontechnology has emerged in response to the need to assist older adults in their daily lives and health care (Ha & Park, 2020). Gerontechnology as is an interdisciplinary academic and professional environment combining gerontology and technical sciences aiming to support sustainability of ageing society by creating technological solutions, including assistive technologies and universal design (Graafmans, Taipale & Charness, 1998). Assistive technologies are home-based systems or devices using ICT that support the independency and well-being of older adults (Bechtold & Sotoudeh, 2013; Bechtold, Capari & Gudowsky, 2017; Halicka, 2019; Halicka & Kacprzak, 2021; Haufe, Peek & Luijkx, 2019; Mostaghel & Oghazi, 2017). These solutions dedicated for older people, can at least partly compensate for their lower functionality physical and mental as well (Piau, Campo, Rumeau, Vellas, & Nourhashemi, 2014; Petermans, 2017; Pressler & Ferraro, 2010). Gerontechnologies combine technologies to improve health, housing, mobility, and communication in order to prevent elderly social isolation and loneliness (Cohen, Kampel, & Verloo, 2016).

Facing global trend of aging population, gerontechnologies will play an increasingly important role in improving the life quality of the elderly (Petermans & Piau, 2017). It is also noteworthy that these technological tools have considerable potential commercial impact. In order to reduce the costs of social care, the concept of aging-in-place is becoming a solution that is being widely promoted among policymakers and representatives of health care institutions (Peek, Wouters, van Hoof, Luijkx, Boeije & Vrijhoef, 2014). Therefore, from the economic perspective, digital technologies, such as e-health and robotics, seem to have the potential to contribute to active and healthy ageing in a cost-effective manner compared with institutional care (American Association of Retired Persons, 2014). As most of seniors would like to spend the rest of their life at home as long as possible, aging at home rather than in an institution is now considered as a desired scenario (Cohen, Kampel & Verloo, 2016). Moreover, gerontechnologies can be applied indirectly for older people through the provision of support to caregivers (European Parliament Technology Assessment, 2019). Potential benefits of assistive technologies are mainly related with increased individual autonomy, comfort, monitoring and safety of older adults (Piau, Campo, Rumeau, Vellas, & Nourhashemi, 2014). Most often robotic technologies assist caregivers or help older people in routine actions in a form of robotic wheelchairs, shower chairs and technologies to prevent falls. Socially assistive robots are more advanced solution using AI, that not only support health care functions but also provide companionship and intellectual agility of seniors. Apart from physical health care, companion robots are also said to enhance mental well-being of older people, so that are often used in therapies for older people having problems with emotional contact and sleeping (Niefeld & Kasper, 2005; Pilotto et al., 2011). Chu et al. (2019) found that older adults had more positive attitude towards service-oriented robots than companion-oriented robots. It is projected that future application of robots seems to be promising, especially for older adults (Chu et. al., 2019).

Nevertheless, implementing health and social care technologies poses many organisational, economic and social challenges. First of all, the main obstacle is the access and use of the internet among older adults differing significantly between countries. For example, in Europe, much more internet users are in northern countries than southern ones. Lack of digital infrastructure in the health and social care sectors is considered as one of the main barriers for the implementing ITC solutions. Moreover, digital alienation among older people, health care workers and caregivers is another challenge, so the programmes of life-long learning to adapt to technologies should be implemented (European Parliament Technology Assessment, 2019). The potential of gerontechnologies has not been yet fully realized because of several economical and organisational barriers limiting their wide implementation like their complexity and high costs of installation and maintenance, the lack of evaluation and validation especially regarding cost-effectiveness and efficiency (Barlow, 2006). Moreover, socio-economic and psychological aspects are relevant for understanding how older people interact with and use technologies (Peek et al., 2019). Sociological barriers for elderly using technology tools are often related with low acceptance of end-users (Ellis & Allaire 1999), inadequate comprehension of seniors' needs and perception (Piau, Campo, Rumeau, Vellas, & Nourhashemi, 2014), threats to privacy (Caine, Fisk & Rogers 2006), security and safety (Miskelly, 2001), and ethical issues including stigmatization and intrusiveness (Piau, Campo, Rumeau, Vellas, & Nourhashemi, 2014). In addition, implementation of robots caries the risks of substituting human assistance by technology and finally increasing user's sense of isolation (Niefeld & Kasper, 2005; Pilotto et al., 2011). Seniors with cognitive impairments have lower acceptance and interest of innovative technology, therefore they often demonstrate negative attitudes toward robots in comparison with other types of technologies such as wearable or mobile devices and environmental sensors (Thordardottir, Malmgren Fange, Lethin, Rodriguez Gatta & Chiatti, 2019; Hebesberger, Koertner, Gisinger & Pripfl, 2017; Wu, Wrobel, Cornuet, Kerhervé, Damnée & Rigaud, 2014). Despite the rapid development of technologies and progressive digitisation of society, the adaptation of new solution by older people still constitutes a great challenge and obstacle to technology implementation on wider scale (Niehaves & Plattfaut, 2014). Other serious concerns of end-users is the cost of assistive technologies, which is related with the economic state of the older people (Hoque, Sorwar, 2017) and their perception of whether the technology is actually 'worth buying' (Mertens, Wille, Theis, Rasche, Finken, Schlick, 2015; Sharma, Nah, Sharma, Katta, Pang, Yong, 2016). Even some elderly would have the will to use assistive technology, the perceived cost of technology would be one of the main barriers, so they would wait for prize drop (Cajita, Hodgson, Lam, Yoo & Han, 2018).

Although the implementation of assistive technologies in silver economy poses many challenges, these technologies seem to be useful and supportive tools solving many problems of aging society. Therefore, the technology acceptance by older people is essential and topical field frequently addressed in scientific research recently. Technology acceptance, which is related to attitude, perception and intention to use technology, is seen as a key concept in understanding the adherence and preference for technology-assisted intervention for older people (Ke, Lou, Tan, Wai & Chan, 2020). Most of the research concerning the impact of beliefs or attitudes on technology use intention by seniors, were based on Technology Acceptance Model (TAM) (Davis, 1985) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis & Davis, 2003). The authors usually examined the perceived usefulness and the perceived ease of use as important predictors for the gerontechnology adoption by the elderly (Ke, Lou, Tan, Wai & Chan, 2020; Mostaghel & Oghazi, 2017; Pan & Jordan-Marsh, 2010; Syed-Abdul et al., 2019). However, the models were often extended with additional constructs such as social norms, perceived enjoyment, expected performance, effort expectation, and trust (Chu et al., 2019; Quaosar, Hoque & Bao, 2018; Syed-Abdul et al., 2019). In order to identify determinants of technology acceptance and adoption by older adults, the researchers combined the TAM and the UTAUT models into the Senior Technology Acceptance Model (STAM). STAM model developed by Renaud and Van Biljon (2008) stated that facilitating conditions, perceived usefulness, and the ease of learning influenced the actual use of new technology, while Chen and Chan (2014a) identified usefulness, ease of use, facilitating condition, and self-efficacy as factors effecting the technology acceptance by older adults.

According to Zhou, Zhang, Tan, Tseng & Zhang (2020), the determinants of the user acceptance behavior can be classified into three dimensions: user individual characteristics, product technical features and environmental characteristics. The attributes of the individual characteristics are summarized as physical, psychological, economic conditions, knowledge and experience. Considering the psychological features of users, male and younger seniors are more often eager to adapt new technologies (Olson, O'Brien, Rogers & Charness, 2011; Pan & Jordan, 2010). Technical anxiety caused by low experience, economic status and knowledge about modern technologies, have a significant negative impact on gerontechnologies adaptation by older adults (Hoque & Sorwar, 2017; Ke, Lou, Tan, Wai & Chan, 2020; Mitzner et al., 2019; Mostaghel & Oghazi, 2017; Pal, Funilkul, Vanijja & Papasratorn, 2018). Older adults' personal characteristics connected with trust and cognitive ability (Ha & Park, 2020; Mostaghel & Oghazi, 2017), and self-efficacy (Ma, Chan & Teh, 2020) have positive impact on behavioral intention towards technology usage. As far as technical characteristics of gerontechnologies are concerned, the researchers explored technical performance or performance expectancy (Li, Ma, Chan & Man, 2019; Talukder, Sorwar, Bao, Ahmed & Palash, 2020; Wang, Tao, Yu & Qu, 2020), effort expectancy and task-technology fit (Wang, Tao, Yu & Qu, 2020), and facilitating conditions (Ha & Park, 2020; Kim, Ferrin & Rao, 2019; Pai & Tu, 2011; Wang, Tao, Yu & Qu, 2020). As the research results revealed, the more complicated product, the higher technical anxiety towards geotechnologies among seniors (Ha & Park, 2020; Wang, Tao, Yu & Qu, 2020). In case of resident-robot, its behavioural engagement moderately influences attitudes towards technology and perceived usefulness (Ke, Lou, Tan, Wai & Cha, 2020; Zhou, Zhang, Tan, Tseng & Zhang, 2020). The environmental characteristics of gerontechologies formulated as 'social influence' and 'subjective norm' constructs, are summarized as the influence of friends or institutions opinions about modern technologies (Cajita, Hodgson, Budhathoki & Han, 2017; Chen et al., 2011; Pan & Jordan-Marsh, 2010; Syed-Abdul et al., 2019; Wang, Tao, Yu & Qu, 2020). Seniors are more susceptible to social environmental influences from family members, friends, and institutions than young people (Zhou, Zhang, Tan, Tseng & Zhang, 2020). Summing up, most of analysed empirical research have proved that perceived usefulness, perceived ease of use, facilitating conditions, self-efficacy and anxiety had impact on older adults' attitude towards usage of general technology and their future intentions (Chen & Chan, 2014b; Chu et al. 2019; Thordardottir et al., 2019; Wu et al., 2014; Zhou, Zhang, Tan, Tseng & Zhang, 2020).

The analysis of available literature has revealed that along with aging society trend, technology acceptance has become popular scientific area in recent years. Nevertheless, further research in this area is needed to better understand the determinants of specific technologies acceptance by older people, especially in the context of design and use of new technological solutions by older people (Ha & Park, 2020; Rogers, Mitzner & Sanford 2014). Increasing older adults' intention to use technologies will bridge the digital divergence caused by aging and rise the penetration of emerging technology products by elderly (Ma, Chan & Teh, 2021). Identifying factors that optimize technology acceptance is essential to improve technology-assisted healthcare, facilitate independent living by older adults and finally solve the problem with the shortage of healthcare staff (Ke, Lou, Tan, Wai & Chan, 2020). Technology usage and adoption by elderly is especially significant in the context of disruptive robot technology, which is still poorly accepted by older people (Beer, Prakash, Mitzner & Rogers, 2011; Chu et al. 2019; Ke, Lou, Tan, Wai & Cha, 2020; Zhou, Zhang, Tan, Tseng & Zhang, 2020).

This article aims to identify the most critical success factors explaining the adoption of an assistive gerontechnology by older adults in Poland. The object of the authors' interest was robot RUDY, which is an AI-enabled mobile solution helping users remain physically healthy, mentally sharp, and socially connected. Rudy is used as a supportive tool for older adults to age in place (https://infrobotics.com/#technology).

RESEARCH MODEL AND HYPOTHESES

The problem of technology acceptance by older adults has been the subject of academic interest in recent years and a number of theoretical models have been developed to explain factors of technology acceptance by older adults (Ma, Chan & Teh, 2020). The original model for studying technology acceptance, including gerontechnology, was model developed by Davis (1985) called Technology Acceptance Model and its modifications (TAM, TAM2, TAM3). Zhou, Zhang, Tan, Tseng & Zhang (2020) proved the importance of technology adoption models such as TAM or UTAUT on gerontechnology.

Considering the specificity of technology acceptance by older people, commonly used technology acceptance models have been adapted to the context of older people. For example, technology acceptance model elaborated by Chen & Chan (2014a) related to technologies used by older people is called as senior technology acceptance model (STAM). Tsai, Rikard, Cotten & Shillair (2019) proposed exploration, learning and acceptance of technology by seniors (STELA). The literature review on gerontechnology acceptance models has confirmed that most researchers consider the three main constructs of the TAM (perceived usefulness, perceived ease of use and attitude) in their models.

Functionality is one of the features of gerontechnology which has to be considered during the process of technology acceptance by elder adults (Beer, Prakash, Mitzner & Rogers, 2011). Pan & Jordan-Marsh (2020) confirmed that perceived usefulness, perceived ease of use are important predictive indicators for the internet adoption of the elderly. Research conducted by Syed-Abdul et. al. (2019) prove that older people consider that using technology should be easy, so their acceptance depends on its usefulness. Ezer, Fisk & Rogers (2009) also found that acceptance was influenced by the perceived advantages in the context of functionalities offered by robots. Syed-Abdul et al. (2019), who analysed factors influencing the intention to use VR among older population, confirmed that perceived usefulness and perceived ease of use were good predictors of future intention to use VR technology by respondents. In many technology acceptance models, the technology functionality is often considered as a performance expectancy. Results received by Peek et. al. (2016) indicated that technology acceptance by older adults was influenced by perception of the technology properties. Research conducted by Wang, Tao, Yu & Qu (2020) confirmed that performance expectancy of healthcare wearable devices found out to be the most important determinant of behavioural intention. According to Peek, Luijkx & Vrijhoef (2019) research, perceived usefulness of technology is more crucial determinant of pre-implementation acceptance, than post-implementation acceptance. Chu et al. (2019) confirmed that in case of ideal assistive robots for older adults' care, users' expectations did not significantly predict their preference of existing robots in terms of perceived usefulness. Arthanat, Wilcox & Macuch (2019) examined the key predictors to smart home adoption by older adults. Their results confirmed that one of smart home functionalities – security – had a significant impact on solution adoption by older people. The study of meta-analysis conducted by Zhou, Zhang, Tan, Tseng & Zhang (2020) on attributes influencing gerontechnology by older adults also proved that perceived usefulness and perceived ease of use had significant positive correlation with attitude toward gerontechnology usage. The above mentioned results are the basis of the following hypothesis:

Hypothesis 1: Perceived usefulness (PU) has a positive impact on attitude attitude reflecting the willingness to use the Robot Rudy

Syed-Abdul et al. (2019) during research on VR technology acceptance confirmed that the older adults are willing to use technology more often if learning and operation of technology is easier. Conci Pianesi & Zancanaro (2009) reported than in case of mobile phone technologies, perceived ease of use was an important factor in the early stage of technology adoption by elderly users. In qualitative research carried out by Cajita, Hodgson, Lam, Yoo & Han (2018), most of participants stated that they would be more likely to adopt m-health if it was easy to use. The ease of use construct in UTAUT technology acceptance models is defined as effort expectancy which refers to the ease related to technology use (Venkatesh, Thong & Xu, 2012). Previous studies have confirmed that effort expectancy has a positive relationship with users' technology acceptance (Hensel, Demiris & Courtney, 2006; Tao, Shao, Liu, Wang, & Qu, 2016). Wang, Tao, Yu & Qu (2020), who examined healthcare wearable devices (HWDs) acceptance by older people, confirmed that effort expectancy significantly affected behavioral intention. Maskeliūnas, Damaševičius & Segal (2019) identified many examples confirming that the success of IoT (Internet of Thinks) use by older people depended on the technology ease of use. The role of this factor becomes less important as the technology is used longer (Karapanos, 2013), but it is important at the initial technology adoption stage. Based on literature review, the following additional research hypothesis was formulated:

Hypothesis 2: Perceived ease of use (PEU) has a positive impact on attitude reflecting the willingness to use the Robot Rudy

Verification of STAM model proposed by Chen & Chan (2014a) confirmed that perceived ease of use (PEU) of gerontechnology had a positive impact on perceived usefulness. Chen & Chan (2014b), who investigated key factors that contribute to gerontechnology acceptance by older residents of Hong Kong, also supported the hypothesis that ease of use had a significant and positive influence on usefulness. It allowed to formulate the hypothesis:

Hypothesis 3: Perceived ease of use (PEU) has a positive impact on perceived usefulness (PU) to use the Robot Rudy

TAM, UTAUT technology acceptance models pay special attention to technical factors related to functionality and ease of use, neglecting social factors at the same time (Davis, 1989; Venkatesh, Morris, Davis & Davis, 2003). However, many studies confirm that social factors play an important role in technology adoption especially by older people (Peek et. al. 2016; Rogers, 2003). Moreover, in the framework of one dominant aging theory – socioemotional selectivity theory – as people get older, they attach more attention to the relational aspects of new technologies than to the technical elements (Carstensen, 1985).

Depending on the context and purpose of the study, researchers expand the initial model with additional variables and examine the relationships between them. Frequently appearing variables in technology acceptance models are: trust in technology, open-mindedness and demographic characteristics of respondents such as age and gender, which significantly determine acceptance of technologies.

Authors of the STAM model (Senior Technology Acceptance Model) proved that personal characteristics played more important role in prediction of users attitude than usefulness and ease of use (Chen & Chan, 2014a). Many research confirmed that individual attributes such as age and gender affect technology acceptance behaviour explicitly and directly (Chen & Chan, 2014a; Ma, Chan & Teh, 2021; Ha & Park, 2020; Mostaghel & Oghazi, 2017).

Being interested and open to new technological solutions determines the attitude of users towards new technologies. Open-minded people are willing to adapt new solutions without fear. Research conducted by Rossi, Staffa, Bove, Capasso & Ercolano (2017) and Rossi, Staffa, Bove, Capasso & Ercolano (2020) confirmed that the openness to experience is directly correlated with robot acceptance.

Older people's trust in gerontechnology is considered by many researchers (Sanders & Scott, 2020). Trust is an important factor reducing the risks and uncertainty associated with technology use (Kim, Ferrin & Rao, 2008; Pavlou, 2003; Salem, Lakatos, Amirabdollahian & Dautenhahn, 2015a). Many researchers found that perceived trust has a significant impact on enhancing older adults' acceptance of robots (Chu et al. 2019; Naneva, Sarda, Gou, Webb & Prescott, 2020; Salem, Lakatos, Amirabdollahian & Dautenhahn, 2015b). Within the Almere model elaborated by Heerink, Kröse, Evers & Wielinga (2010) trust to assistive robots is one of the factors influencing elderly users' acceptance and attitude towards socially assistive robots. Chu et. al., (2019) studied trust in two categories of robots: human-like and service-oriented robots. According to Lie, Lindsay & Brittain (2015) trust emerged as a key factor in the acceptance of home monitoring system tested by older adults.

Taking into account above results, the relationships between the analysed three main variables (ease of use, usefulness and attitude) was statistical verified. Moreover, the model included the controlled variables, such as: age, gender, level of technology knowledge (Question: Did you hear about Robot Rudy?), declared level of trust to technology and openness to new technologies.

Theoretical model that reflects the links between all the variables is presented on figure 1.

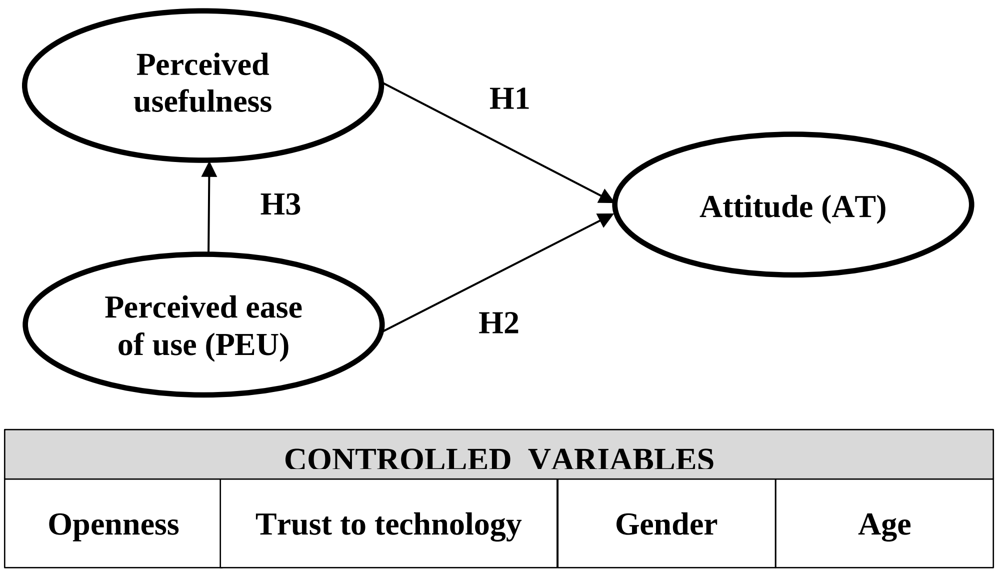


Figure 1. Conceptual model

RESEARCH METHOD

Data

Data was collected using the CATI (*Computer Assisted Telephone Interviewing*) technique. Telephone interviews were conducted with residents of Poland. The research was carried out by a research company between November and December 2020. Taking into account the type of gerontechnology under study and the fact that for a large part of the respondents this technology could be foreign and unknown, during the phone interviews (mainly conducted on the mobile phones) the image of Robot Rudy was sent to the respondents in the form of a text message. Only for a few respondents, the interviewer presented Robot Rudy in a descriptive form.

The interviews were carried out on the basis of structured questionnaire forms among 1521 Polish citizens, but finally 824 questionnaires without missing data were accepted for further analysis.

The structure of research sample was balanced in terms of respondents' gender and age. Within research sample, 450 of respondents (54.6%) were women, and 374 were men (45.4%). The gender structure of the respondents is similar to general population of Polish society, in which women constitute 51.6%, and men 48.4%. The study sample and its balanced gender structure determines the study results and enables to avoid research bias (Ma, Chan & Teh, 2021).

People over the age of 40 took part in the study for two reasons: these people have parents who need care or they may need care in the perspective of next 20-30 years. Young people were excluded from the study, as the problem of technologies adaptation aimed at improving the lives of the elderly, have not concerned them yet. Respondents aged 41-50 amounted to 26.7% (220 persons), 28.8% (237 persons) were 51–60 years old, 44.5% (367 persons) were over 60.

The respondents structure was diversified considering the levels of education. People with primary education constituted 3.8% (31 persons), with vocational education – 22.0% (181 persons), with secondary education – 45.2% (350 persons) and with higher education (university level) – 31.8% (262 persons). Respondents also represented different status by place of their residence. 19.1% of respondents (157 persons) indicated a village as their place of residence, 12.0% (99 persons) lived in a city with less than 20 thousand inhabitants, 15.5% (128 persons) – in a city with 21-50 thousand inhabitants, 18.2% (150 persons) – in a city with 51-150 thousand inhabitants, 9.1% (75 persons) – in a city with 151-250 thousand inhabitants and 26.1% indicated a city with more than 250 thousand inhabitants as a place of their residence.

Respondents' awareness of the surveyed technology was evaluated using the following question: Have you ever heard about Robot Rudy (https://infrobotics.com/#Rudy)? Only 6.1% of respondents answered positively to this question. The remaining 93.9% responded negatively. As the majority of respondents had not heard about Robot RUDY, before proceeding the interview, the interviewer described the robot appearance and functionality in relation to elder care.

Measures

As the constructs included in the theoretical model could not be directly observed, a set of variables were used to analyses relationships between constructs. Based on the literature study, five items have been identified to measure the perceived usefulness of the studied technology

(PU), two — perceived ease of use the studied technology (PEU) and three — attitude reflecting the willingness to use the studied technology (AT).

Variables within two constructs: perceived usefulness and perceived ease of use were measured using a seven-point Likert scale to evaluate the degree to which a respondent agreed or disagreed with each of the items (1 = totally disagree; 7 = totally agree). Variables regarding the attitude constructs were measured using scale: 1 - definitely not, 2 - rather not, 3 - rather yes, 4 - definitely yes.

Elaborated on the basis of the literature review, the variables within particular constructs were subject to confirmatory factor analysis (CFA). The aim of the CFA was to verify and confirm the structure of the adopted factors. The parameter values were estimated using the generalized least squares (GLS) estimator, due to its lower sensitivity to normal-distribution assumptions. Variables for which the value of the regression coefficient was lower than 0.6, and for which the standardized residual covariances were greater than 2 were removed from the original set of observable variables.

Cronbach's alpha coefficients was used to verify the consistency of the items in the scale. It is assumed that Cronbach's alpha coefficient above 0.7 is acceptable, and if it is less than 0.7 it suggests that the item of the scale needs to be revised. For convergence validity two indicator were used: Avarage Variance Extracted (AVE) proposed by Fornell & Larcker (1981) and Composite Reliability (CR). Average Variance Extracted (AVE) is greater than 0.5, indicating that the measurement can better reflect the characteristics of each research variable in the model. When CR is greater than 0.7, it indicates that the inherent consistency of all measurement is higher (Hair, Black, Babin, Anderson & Tatham, 2013).

The scale reliability was reflected by Cronbach's alpha ranging from 0.749 to 0.945. Composite Reliability (CR), Average Variance Extracted (AVE) were also higher than expected, which confirmed the convergence validity of scale. Descriptive statistics, composite reliability and convergence validity for the constructs and items are presented in Table 1.

Table 1. Descriptive statistics, Cronbach's α, Composite Reliability and Avarage Variance Extracted.

Constructs and Items	Mean (M)	Factor Loading	Cronbach's α	Composite Reliability (CR)	Avarage Variance Extracted (AVE)
Perceived usefulness (PU) (Mostaghel & Oghazi, 2017; Syed-Abdul et al., 2019; Chen & Chan, 2014a; Chen & Chan, 2014b; Hoque & Sorwar, 2017)					
PU1: If I had to, using Robot Rudy would improve my sense of security	5.18	0.865	0.945	0.925	0.713
PU2: If I had to, using the Robot Rudy would give me more autonomy	5.32	0.872			
PU3: If I had to, using the Robot Rudy would give me the ability to ask for assistance	5.57	0.814			
PU4: If I had to use the Robot Rudy I would feel self-confident and independent	5.26	0.939			
PU5: If I had to use the Robot Rudy I would feel safer	5.22	0.921			
Perceived ease of use (PEU) (Mostaghel & Oghazi, 2017; Syed-Abdul et al., 2019; Chen & Chan, 2014a; Chen & Chan, 2014b; Hoque & Sorwar, 2017)					
PEU1: It would be easy for me to obtain the ability to use Robot Rudy	5.22	0.939	0.749	0.782	0.650
PEU2: I would gain the ability to use the Robot Rudy without the help of others	4.81	0.647			

Attitude (AT) (Syed-Abdul et al., 2019; Chen &Chan, 2014a; Heerink, Kröse, Evers & Wielinga, 2020)					
AT1: I would be willing to use Robot Rudy to assist a member of my family	2.98	0.899	0.905	0.821	0.764
AT2: I would be willing to use Robot Rudy myself as a person who needs it	3.10	0.900			
AT3: There is a need to construct Robots Rudy	3.11	0.821			

The highest rated robot functionalities were as follows: the Robot would enable their users to ask for assistance (mean - 5.57) and the robot would give me more autonomy (5.32). On average, respondents expressed a modest attitude towards assistive robot, since the mean scores (on a 1–4 scale) were 2.98 for willing to use Robot Rudy to assist a member of family, 3.10 for willing to use Robot Rudy yourself and 3.11 general need to construct Robot Rudy.

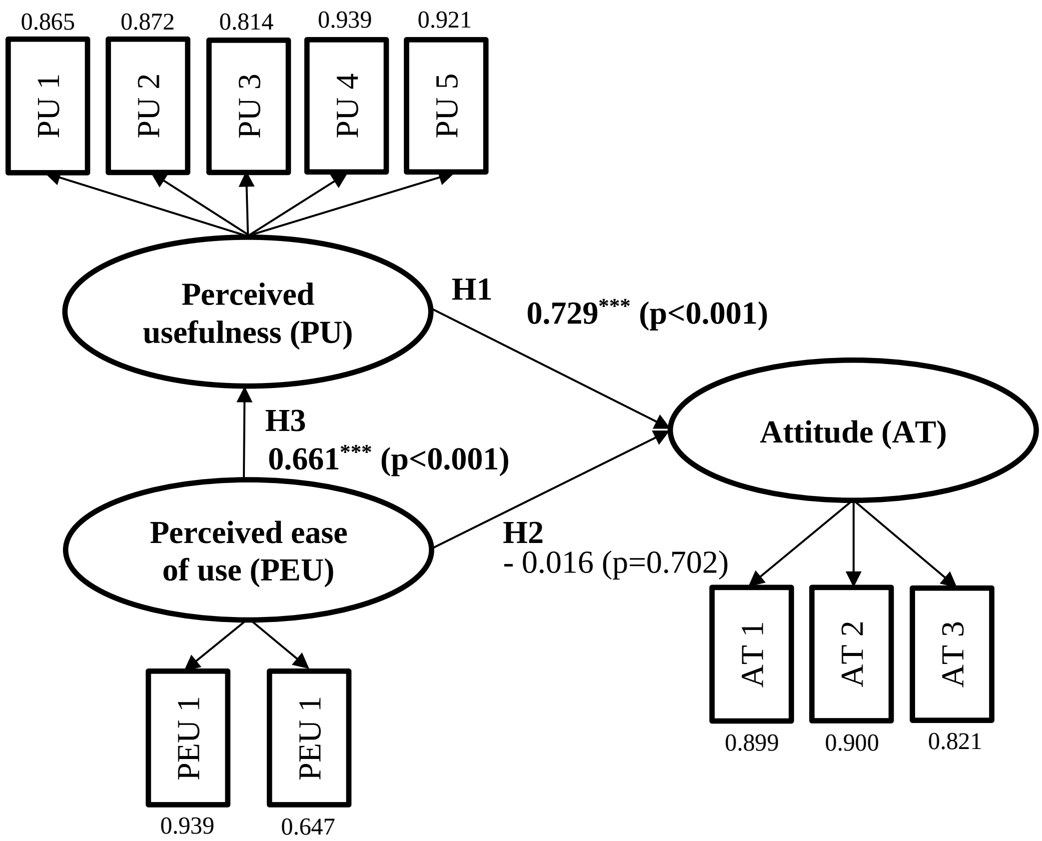
RESULTS

The appropriateness of the measurement model was evaluated by using the Chi-Square statistics. The $\chi 2$ value was statistically significant ($\chi 2=81.927$, $p<0.001$) indicating a good model fit to the data. Also, ratio chi-square divided by the degrees of freedom ($\chi 2/df$) was used as a measure of model fit, with values of 3 or less indicates a good model fit. Ratio $\chi 2/df$ achieved the value of 2.643 which proved the good fit of model as well. According to the Bollen (1989), several disparate indices had been taken into consideration to evaluate an overall model fit. The indices adopted to assess the SEM model fit and their desired values, are presented in Table 2.

Table 2. Model fit indices**.**

Model fit indices	Level of acceptance	Sources	Ratio achieved
Chi-Square/Degrees of freedom ($\chi 2/df$)	desire < 3, acceptable < 5	Iacobucci, 2020	2.643
Comparative fit index (CFI)	0.9, 0.95 desire	Schumacker, Lomax, 2010; Hu, Bentler, 1999	0.939
Root mean square error of approximation (RMSEA)	0.05 (0.08)	Konarski, 2010; Bollen, 1989	0.045
The goodness-of-fit index (GFI)	>0.9	Jöreskog, Sörbom, 1979	0.980
The adjusted goodness-of-fit index (AGFI)	>0.9	Jöreskog, Sörbom, 1979	0.965
Standardized Root Mean Residual (SRMR)	<0.09	Hu, Bentler, 1999; Browne et. Al., 2002	0.021

The hypotheses have been confirmed through the interpretation of the structural path coefficients. Relationships between perceived usefulness of Robot Rudy and attitude reflecting the willingness to use this technology and between perceived ease of use and perceived usefulness of Robot Rudy were statistically significant ($p < 0.001$). Thus, these positive relationships confirmed hypotheses H1 and H3. Relationship between construct perceived ease of use and attitude reflecting the willingness to use this technology was not statistically significant ($p = 0.702$). Hypothesis H2 was rejected (table 3). Fig. 2 presents the individual structural path estimates between constructs and variables.



Values on paths between latent variables are standardised regression coefficients and values at observable variable are factor loads.

Figure 2. Measurement model.

Table 3. Results of the test hypotheses**.**

Relationship between Constructs	Estimate	Standard Error	Capability Ratio	p	Hypothesis Testing
H1: PU→AT	0.344	0.021	16.767	***	Support
H2: PEU→AT	-0.011	0.028	-0.383	0.702	Reject
H3: PEU→PE	0.923	0.060	15.489	***	Support

χ^2 = 81,927; degrees of freedom (df) = 31; χ^2/df = 2,643; $p < 0.001$; root-mean-square error of approximation (RMSEA) = 0.045; goodness-of-fit index (GFI) = 0.980; *** the adopted level of statistical significance was 0.001

The Mann-Whitney U test was used to verify relationships between all analysed variables and respondents' gender. Statistically significant differences were found in the level of assessment variables PU3 and PU4 between respondents of different genders (PU3: Z = -2.812; p** < 0.05; PU4: Z = -3.367; p** < 0.05). Analysis of mean rank confirmed that women assess higher the functionality of Robot Rudy reflecting the ability to ask for assistance (PU3) and making them feeling self-confident and independent (PU4) than man (table 4).

A non-parametric ANOVA Kruskal-Walls test was used to examine statistically significant differences in assessment of all analysed variables across age groups. Only in case of variable PU3 (If I had to, using the Robot Rudy would give me the ability to ask for assistance) such statistically significant difference was found (chi-square = 9.664, df = 2; p** < 0.05). Differences in mean ranks across age groups confirmed that older respondents at the age between 51-59 year and above 60 years old, assessed this functionality of Robot Rudy at higher level than younger respondents – at the age of 41-50 years old (table 4).

During the research, two additional grouping variables were taken into account. One variable reflected the level of respondents' trust to Robot Rudy, second reflected respondents' openness to new technology. Results of ANOVA Kruskal-Walls test confirmed that there is statistically significant differences in grading all analysed variables and the level of trust and openness. Respondents who declared higher levels of trust and openness to new technologies gave higher scores to the analysed variables relating to functionality, ease of use and attitude reflecting the willingness to use the studied technology (table 4).

Table 4. Asymptotic significance.

Constructs and Items	Gender	Age	Did you hear about Robot Rudy?	I would be able to trust Robot Rudy	I am open to new technologi cal solutions
AT1: Would you be willing to use Robot Rudy yourself to assist a member of your family?	0.142	0.494	0.005**	0.000***	0.000***
AT2: Would you be willing to use Robot Rudy yourself as a person who needs it?	0.528	0.757	0.000***	0.000***	0.000***
AT3: Do you think there is a need to construct Robots Rudy?	0.376	0.188	0.030	0.000***	0.000***
PU1: If I had to, using Robot Rudy would improve my sense of security	0.011	0.024	0.404	0.000***	0.000***
PU2: If I had to, using the Robot Rudy would give me more autonomy	0.015	0.098	0.844	0.000***	0.000***
PU3: If I had to, using the Robot Rudy would give me the ability to ask for assistance	0.005**	0.008**	0.173	0.000***	0.000***
PU4: If I had to use the Robot Rudy I would feel self-confident and independent	0.001**	0.145	0.928	0.000***	0.000***
PU5: If I had to use the Robot Rudy I would feel safer	0.089	0.160	0.859	0.000***	0.000***
PEU1: It would be easy for me to obtain the ability to use Robot Rudy	0.269	0.054	0.097	0.000***	0.000***
PEU2: I would gain the ability to use the Robot Rudy without the help of others	0.898	0.368	0.263	0.000***	0.000***

******* the adopted level of statistical significance was 0.001

****** the adopted level of statistical significance was 0.05

DISCUSSION

The conducted research confirmed that the functionality of the analysed technology Robot Rudy for older adults care positively influences their attitude about its future use - for their own needs or their family members. The positive relationship between the technology functionality and the users' attitudes towards using the analysed technology, confirmed by the study, is consistent with the results of other authors. In research conducted by Chen & Cha (2014a) perceived usefulness had a significantly positive effect on attitude toward using technology. In the opinion of Mitzner et al. (2019) the positive attitudes toward using technology by older adults are associated with the technology usefulness and how the technology can support their activities and enhance convenience. Research conducted by Ma, Chan & Teh (2021) confirmed that older adults' usage intention toward information technology was based on technology usefulness in the context of improving their life quality. All measured functionalities of Robot Rudy in our study were assessed at a very similar level. The average rate varied from 5.18 (Robot Rudy would improve my sense of security) to 5.57 (Robot Rudy would give me the ability to ask for assistance).

The authors' results are different from the results obtained by Chu et al. (2019), who confirmed that in case of ideal assistive robots for older adults care, users' expectations did not significantly predict their preference of existing robots in terms of perceived usefulness. In the case of the authors' research, the analysed robot is a technology used currently with specific appearance and functionality. In the conducted research, however, taking into account the low level of familiarity of the respondents with the analyzed gerontechnology- Robot Rudy, the vast majority of them had the opportunity to see the robot through a text message sent by the interviewer. Simply seeing the technology may have have influenced the declared evaluation of the technology's functionality, ease of use and users' attitudes.

As in most technology acceptance models, the results of the present study also confirmed that the perceived ease of use (TAM model) or effort expectancy (UTAUT model) of technology have impact on the perceived usefulness of the technology (TAM model) or performance expectancy (UTAUT model) (Chen & Chan, 2014a; Chen & Chan, 2014b; Hoque & Sorwar, 2017).

However, our study proved that there is no relationship between perceived ease of use of technology and attitudes towards its future use in elderly care. The results based of qualitative research of Cajita, Hodgson, Lam, Yoo & Han (2018) also indicated that perceived ease of use and perceived usefulness did not influence solely the intention of the older adults to use m-health. Similarly, results achieved by Ha & Park (2020) revealed that perceived ease of use was relatively lower than attitude towards technology using or perceived usefulness (Ha & Park, 2020). On the other hand, the obtained results are contrary to the findings of other authors. Results gained by Chen & Chan confirmed that perceived ease of use positively affected perceived usefulness and attitude toward using technology as well (Chen & Chan, 2014a). According to the results achieved by Ma, Chan & Teh (2021), the acceptance of information technology by older adults was considerably related with ease of use. Study conducted by Hoque & Sorwar (2017), who analysed factors affecting adaptation of m-health services by older adults, confirmed that performance expectancy had a significant impact on the users' intention to adopt m-health services.

Assessments of relationships between ease of use and propensity to technology adaptation vary and depend on many factors. This diversity often results from a greater role attributed to the technology functionality under study than ease of use. In addition, the strength of the relationship between the constructs is influenced by many other factors, such as the type of technology, its level of dissemination, and users' skills resulting from previous experience, age, level of technological education or willingness to learn.

Age was a controversial moderator in the past studies (Ma, Chan & Teh, 2021) connected with the gerontechnology acceptance. Research conducted by Ha & Park confirmed (2020) that age was significant factor predicting technology acceptance. Research conducted by Mostaghel & Oghazi (2017) show that all the age-related attributes are important to perception of technology ease of use and its usefulness. In the study by Heerin, Kröse, Evers & Wielinga (2010), older adults were less willing to use robots than their younger counterparts. Among the demographic characteristics within research conducted by Ha & Park, age (r = -0.241) and education (r = 0.941) were significantly associated with technology acceptance (Ha & Park, 2020) According to Ma, Chan & Teh (2021), age of the respondents measured directly on a chronological scale, was not an appropriate indicator.

Results of systematic literature review conducted by Naneva, Sarda, Gou, Webb & Prescott, (2020) indicated that the age of participants was not significantly associated with their affective attitudes toward social robots. In the present study authors' confirmed similarly to Chen & Chan (2014) that age effects on other constructs were not significant. Only in case of functionality reflecting the ability to ask for assistance statistically significant difference was found. In this case, older respondents (at the age between 51-59 year and above 60 years old) assessed this functionality at higher level comparing younger respondents – at the age of 41-50 years old. Results achieved by Chen & Chan (2014a) also proved that age was found to be negatively associated with perceive ease of use, perceived usefulness and attitude towards using gerontechnology, but the age effects on perceived usefulness and attitude were not significant.

Gender of respondents is often a control variable in technology acceptance research. The results of other authors are often ambiguous and characterised by variability depending on the technology type tested. Chen & Chan (2014a) found that males were more likely to use gerontechnology than females, however there were no gender differences with regard to attitudes towards technology.

Research on trust in assistive technologies seems important given that people are more likely to rely on technologies when those technologies are trustworthy (Schwaninger, Güldenpfennig, Weiss & Fitzpatrick, 2021; Salem, Lakatos, Amirabdollahian & Dautenhahn, 2015). Trust between the user and the robot was identified as important in human-robot interaction and in human-human interactions in therapy (Langer, Ronit Feingold-Polaka, Mueller, Kellmeyer & Levy-Tzede, 2019). The study confirmed that the declared trust in Robot has a positive effect on variables reflecting their perceived ease of use, functionality and attitude of technology.

The results of present study proved that openness to new technological solutions had a statistically significant effect on all study variables. Similar results indicating a relationship between openness and robot acceptance were obtained by Rossi et al. (2020).

The limitations of the conducted research are particularly related to the respondents' declared assessments of the functionality and ease of use of the robots, which does not always reflect their real later behaviours.

The research technique using CATI also provided limited insight to the respondents about the technology under study. They expressed their opinions based on the image of the technology, without having in-depth knowledge of its functionality. Only individual experience with the use of the technology would allow for more in-depth research results.

The relationships between the technology acceptance variables are often dependent on the technology itself and its functionality. Lack of willingness to use technology often results, on the one hand, from the lack of perceived benefits from its use and, on the other hand, from limited confidence in the ability to acquire the skills to use it. To familiarize the elderly with new technologies, it is necessary to develop information channels that present the functionality of technologies and the benefits of their use in the context of improving safety, independence and supporting care at their own home.

In the context of the studied variables, the characteristics related to the openness of older people to new solutions should be analyzed in more detail. Although the results obtained did not confirm the relationship between the age of the respondents and the studied variables, in future research the age of the respondents should be referred not to the chronological scale but to the physical and psychophysical age of the respondents.

Conducted research was also an element of building public awareness of Poles in the potential use of gerontechnology by the elderly and improve their comfort and quality of life.

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VR-ORIENTED EEG SIGNAL CLASSIFICATION OF MOTOR IMAGERY TASKS

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Abstract: *Virtual Reality (VR) combined with near real-time EEG signal processing can be used as a supplement to already existing rehabilitation techniques, enabling practitioners and therapists to immerse themselves into a virtual environment together with patients. The goal of this study is to propose a classification model along with all pre-processing and feature extraction steps, which would be able to produce satisfying results while maintaining near real-time performance. The proposed solutions are tested on an EEG signal dataset containing left/right-hand motor imagery movement experiments performed by 52 subjects. Performance of different models is measured using accuracy scores and execution time both in the testing and the training phase. In conclusion, one model is proposed as optimal given the requirements of potential patient rehabilitation procedures.*

Keywords: *real-time EEG analysis, Virtual Reality, CSP filtering, motor imagery.*

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INTRODUCTION

The concept of a brain-computer interface (BCI), which enables users to communicate and interact with the environment, bypassing the normal somatosensory pathways, dates back to the late 1970s. Since then, it has been significantly developed both in terms of signal acquisition methods and potential application areas. The acquisition methods include invasive approaches – in which the electrodes are surgically implanted either above the cortex (electrocorticography, ECoG) or directly in the grey matter of the brain – and non-invasive ones. The latter methods, including most prominently the electroencephalography (EEG), typically suffer from reduced spatial resolution and poor signal-to-noise ratio. Despite this, EEG is currently the most widespread signal source used in a range of BCI applications.

One of the important application areas, as far as EEG-based brain-computer interface is concerned, is motor imagery task recognition and classification. Mental simulation of the physical movements of body parts (Decety, 1996) involves imagined activation of muscle groups without their actual activation. It is employed, for example, in sport and music training, but also as an important part of the neurorehabilitation process in several medical conditions involving motor deficits, such as multiple sclerosis and stroke.

Integrating BCI with immersive virtual reality (VR) environments is a particularly interesting research area that creates opportunities for enabling post-stroke patients to control the virtual representation of the paralyzed limb, which may lead to increased stimulation, motivation for training and enhanced rehabilitation outcomes (Wojciechowski, Wiśniewska, Pyszora, Liberacka-Dwojak, & Juszczyk, 2021).

Successful VR-BCI integration requires solutions to several technical problems, including the choice of the equipment for EEG signal acquisition and virtual reality simulation that would correctly operate in terms of physical characteristics, electromagnetic compatibility, etc. The most critical parameters or – more precisely – evaluation measures that must be considered are accuracy of motor imagery task classification and processing time. The first element is especially important, as due to the generally low quality and poor resolution of the input EEG signal statistical and machine learning approaches are typically used here to reliably extract the target information (Opałka, Stasiak, Szajerman, & Wojciechowski, 2018; Zhang, Yan, & Gong, 2017). Processing time, on the other hand, also cannot be neglected, as the real-time operation is a *sine qua non* condition in all practical VR applications, significantly influencing the user's experience and the sense of immersion.

In this work, we present a study on EEG-based motor imagery task classification for potential applications in a virtual reality environment targeted at post-stroke neurorehabilitation support. Several design principles and configurations of the feature-extraction/classification process are investigated, including electrode and frequency band selection, signal preprocessing methods and the choice of the classifier. Common spatial pattern (CSP) was selected as the primary tool for data dimensionality reduction and feature extraction. The obtained results enabled us to formulate some important and practically useful conclusions regarding the design of the consecutive processing stages and appropriate parameter settings.

BASIC CONCEPTS AND PREVIOUS WORK

The history of brain-computer interfaces (BCI) starts with the first observations of the spontaneous brain electrical activity and – most prominently – with the acquisition of the first human EEG signal, recorded by Hans Berger in 1924 (Haas, 2003). The general idea and the term "brain-computer interface" itself were proposed by Jacques Vidal (1973, 1977). Along with the technological development of devices and signal processing methods, new application areas emerged, including BCI-based video games (Kaplan, Shishkin, Ganin, Basyul, & Zhigalov, 2013; Liao, Chen, Wang, Chen, Li, Chen, Chang, & Lin, 2012; Van de Laar, Gurkok, Bos, Poel, & Nijholt, 2013) and interaction support in virtual reality environments (Cattan, Andreev, & Visinoni, 2020; Lécuyer, Lotte, Reilly, Leeb, Hirose, & Slater, 2008). User interaction typically involves one of the three dominant BCI paradigms: steady-state-visually-evoked-potentials (SSVEP), P300 event-related potentials (ERP), and mental imagery (Cattan et al., 2020). From our point of view, only the latter case is of interest, as it involves voluntary action of the user, without the need for specific stimulus preparation, such as e.g. oscillatory patterns used in SSVEP. The P300 wave (ERP), although not targeted directly in our research, is however of some interest to us, as it appears in response to visual stimulation used during the data collection procedure. ERP is best described as time-locked changes in the activity of neuronal populations in response to a sensory, motor or cognitive event (Pfurtscheller & Da Silva, 1999). This evoked activity, or signal of interest, has a fixed time delay to the stimulus. Locking ERP in time allows extraction of stimuli-related brain activity in the form of EEG signal data. For VR-based applications, ERPs will typically be induced by visual or auditory stimuli. An immersive VR environment ensures that no additional stimuli (i.e. not generated by the VR itself) will be present. Finding potential ERPs in the EEG signal acquired during experiments in the virtual environment can be used as a base to create a BCI capable of classifying brain activity. From the technical point of view, two important subtypes of the ERP phenomenon may be distinguished: Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS).

Event-Related Desynchronization can be defined as decreased synchrony of the underlying neuronal populations. The exact phenomena behind it are a series of transient postsynaptic responses of main pyramidal neurons triggered by a specific stimulus. It can be observed as power decrease in the signal of the electrode over a given neuronal population.

During hand movement, contralateral desynchronization can be observed in the upper *alpha* (*mu*) band (in the range of about 10-12Hz) close to the hand sensorimotor area. This ERD is present in nearly every subject and can reliably be used in classification tasks. Another contralateral ERD can be observed in lower *beta* (in the range of about 20-24Hz) in a similar location to the *mu* band ERD, only slightly anterior. These ERDs will not be present after performing of the task is stopped.

Event-Related Synchronization occurs when synchrony of the underlying neuronal populations increases. Similarly to the ERD, it can be considered as a series of transient postsynaptic responses of main pyramidal neurons triggered by a specific stimulus and it can be observed as a power increase in the signal of the electrode over a given neuronal population.

ERS is usually associated with the rest state of neuronal populations. ERS behaviour can be described as antagonistic to ERD. While observing contralateral ERD in the *beta* band (18-26Hz) in motor or motor imagery tasks we can also observe ipsilateral ERS in the same band. Furthermore, while performing self-paced hand movements in which *mu* band ERD can be observed, *alpha* band ERS in the occipital area occurs. Another ERS with a relatively good signal-to-noise ratio is post-movement *beta* ERS which can be observed in the corresponding sensorimotor area in the first second after the termination of a voluntary movement while *mu* band ERD is still present.

In the rest of this paper, we consider a problem of EEG signal classification involving three classes (rest state, left-hand motor imagery and right-hand motor imagery). We decided to target hand imagery movement over e.g. left/right foot movement, because neuron populations in the motor cortex areas related to hand movements are larger, hands can perform a higher variety of movements and visualization of hands is easier in a VR environment.

METHODS

Electrode selection

The choice of the appropriate location for the EEG electrodes is particularly important and not straightforward, especially while targeting higher-order cognitive processes or emotional state recognition (Dura & Wosiak, 2021). In our case, however, the area of interest is clearly defined as the primary motor cortex, although the potential benefits of using a broader selection of EEG channels are also considered, as stated below.

It should also be noted that both VR and BCI devices are mounted on the user's head, which may potentially cause some compatibility issues. VR headsets usually come with a head strap that goes around the head just over the ears. Some of these devices have additional support straps connected either to the VR device and the middle of the main strap (i.e. in the median plane) or to the main strap near the ears running parallel to the VR headset (i.e. in the frontal plane). The latter setting may impose some compatibility problems when used along with the BCI interface, as the additional strap (if it cannot be removed) covers the area coincident with the motor cortex.

Two EEG electrodes that are located directly in the areas of the main activity during motor imagery hand movements are C3 and C4 (Fig. 1). We decided to test 4 sets of electrodes:

- 2 channel configuration including C3 and C4, marked by red dots in Fig. 1;
- 10 channel configuration including FC3, C5, C3, C1, CP3, FC4, C2, C4, C6, and CP4, marked as red and green dots in Fig. 1;
- 18 channel configuration including FC5, FC3, FC1, C5, C3, C1, CP5, CP3, CP1, FC2, FC4, FC6, C2, C4, C6, CP2, CP4 and CP6, marked by red, green and blue dots in Fig. 1;
- 64 channel configuration including all 64 available channels. This configuration includes all the electrodes in Fig. 1.

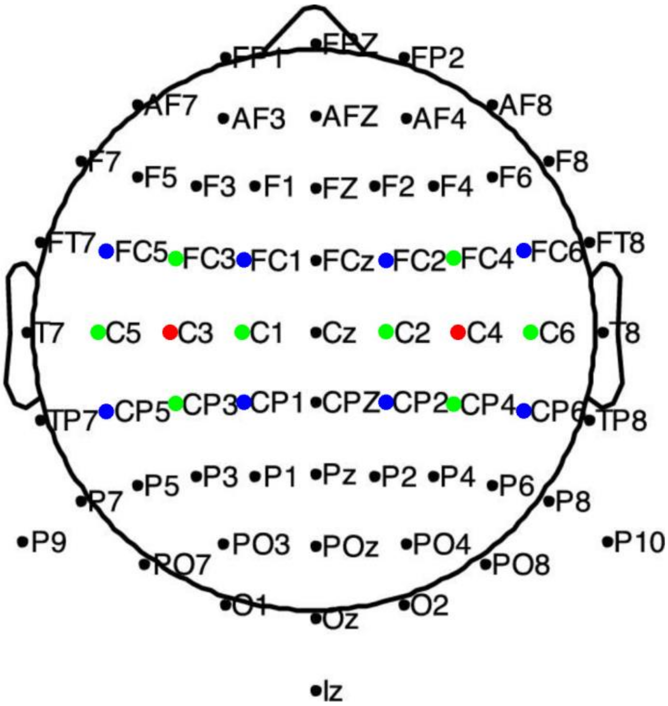

Figure 1. Biosemi64 configuration of EEG electrodes with selected channels highlighted.

The first set is meant to represent the bare minimum to attempt the motor imagery classification task. The second and the third sets represent configurations of electrodes that allow wearing both BCI and VR devices. The last set is used to show how the task can be performed without constraints imposed by the VR headset mount. It should be noted, however, that selecting too many channels can negatively affect near real-time performance which is expected from BCI.

High-pass and band-pass filtering

EEG data is prone to be affected by drifts as it is a recording of electrical activity. To remove these drifts, a high-pass filter with a cutoff frequency of 1Hz is used. Then we apply a band-pass filter with a lower cut-off frequency of 6Hz and a higher cut-off frequency of 30Hz. Frequencies lower than 6Hz are below *mu* band (apart from toddlers that can have *mu* band as low as 5.4Hz but they are not in the subject group) and frequencies higher than 30Hz (upper limit of *beta* waves) do not carry any valid information from our point of view. It is also worth noting that stationary 50/60Hz powerline background frequency, which highly influences any electrical activity recordings, is far above the 30Hz cutoff. Apart from this 6-30Hz filtering, the experiments described in the following sections apply additional band-pass filtering if necessary.

Re-referencing algorithms

EEG recordings are usually performed using a common reference placed somewhere on the head. Some of the possible placements include e.g. vertex (CZ) or linked-ears. We can also omit using the referencing electrode and use one of many existing reference-free techniques. In our research, we use a reference-free method called Common Average Reference (CAR), as it is suitable for all chosen channel configurations. We can apply CAR by removing the mean of all the electrodes from each EEG channel. An example of CAR calculation for the C3 channel (in 10 channel configuration) is shown in Eq. (1).

$$C3_{(CAR)} = C3 - \frac{FC3+C5+C3+C1+CP3+FC4+C2+C4+C6+CP4}{10} \tag{1}$$

For any other configuration, involving a different number of EEG channels, CAR is computed in a similar way.

Common Spatial Pattern filtering

CSP filtering is one of the most frequently used feature extraction algorithms in EEG data binary classification tasks (Alhaddad, 2012). It transforms a band-pass filtered EEG signal into a spatially filtered space. The goal of this transformation is to maximize the individual output signal variance for one class while minimizing it for another class. In fact, the CSP output consists of the same number of channels as the original input signal, but they are sorted by the variance ratio between the two classes. In this way, a low-dimensional linear subspace maximizing the variance ratio may easily be defined and used instead of the original space spanned by all EEG channels. In our approach, the average power of each CSP filter is calculated to obtain an n-dimensional feature vector, where n is the number of CSP filters.

When ERS occurs in a signal, increased signal variance can be observed. On the other hand, ERD will cause desynchronization of the signal, thus reducing the variance. As the main principle of the CSP filter is to maximize the variance for one class and minimize it for the other, both ERS and ERD play a crucial role here, constituting jointly the fundamental mechanism underlying the actual effectiveness of the CSP-based feature extraction.

CSP has been initially proposed for a two-class scenario. This poses a challenge for classification involving three classes (rest, imagery movement left, imagery movement right). One possible solution would be to split the classification problem into two subproblems, solved by two classifiers consecutively. The first classifier would distinguish between the rest class and imagery movement class and the latter class would be further classified by the second classifier making decision between left and right imagery hand movement. Another solution would be to use multiclass CSP filters. Such a multiclass filter was proposed by Grosse-Wentrup and Buss (2008).

It should be noted that CSP can only be used to reduce the dimensionality of the original signal space. There cannot be more CSP channels than signal sources (electrodes). Therefore, in 2 channel configuration, we use both available output CSP channels (no dimensionality reduction), while in the other configurations (10, 18 and 64 channels) we are using the fixed number of 10 CSP filters with the highest variance ratio.

Hierarchical model

Three-class classification problem cannot be directly solved using a binary CSP – hence, a hierarchical approach was applied. The first step was to classify whether the analysed signal comes from the rest state or an imagery movement (left and right imagery movements combined into one class). When the rest state was detected, it was returned as a result, while an imagery movement needed to be further classified into left or right by another binary classifier. This hierarchical approach can be seen in a diagram in Fig. 2.

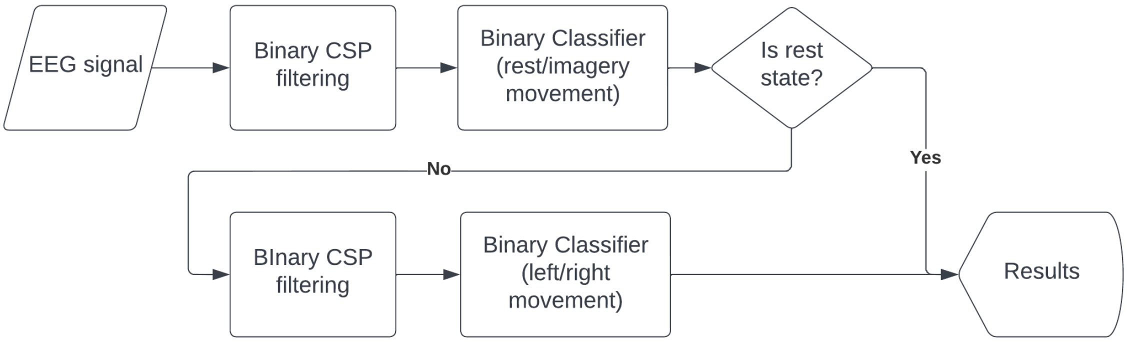

Figure 2. Hierarchical classification workflow for binary CSP filters.

Multiclass model

An alternative implementation of the multiclass CSP filter proposed by Grosse-Wentrup and Buss (2008) simplifies the classification problem, making the hierarchical approach unnecessary. After EEG signal preprocessing with multiclass CSP filters, the classifier is used to label the output data (Fig. 3). In our classification-ready dataset, extracted from an EEG dataset for motor imagery brain–computer interface (Cho, Ahn, Ahn, Kwon & Jun, 2017), the number of the rest state examples is twice the number of either left or right motor imagery examples, as described in the next chapter. A multiclass model working on this whole dataset will be referred to as *multiclass unbalanced*. Another, smaller dataset is derived from our main classification-ready dataset so that the number of the rest state examples is reduced to match the number of left or right imagery movement examples. A model working on this balanced set will be referred to as *multiclass balanced*.

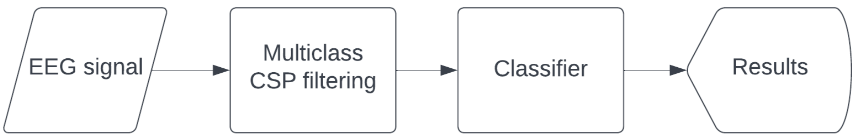

Figure 3. Multiclass classification workflow for multiclass CSP filters.

Classifiers

In our experiments, two popular classifiers were applied: linear discriminant analysis (LDA) and a multilayer perceptron (MLP).

Linear discriminant analysis has also been used by the authors of the original dataset (Cho et al., 2017) for binary classification task (left/right imagery hand movement). LDA searches for a linear combination of predictors that separates two classes in the best way. It is considered a simple yet robust classifier, often able to compete with many more complex methods.

The multilayer perceptron is a powerful non-linear classifier which, as the name suggests, is a neural network with multiple layers of artificial neurons. It may be trained, with appropriate machine learning algorithms, to discover deeply hidden patterns in complex multidimensional input data. It should be noted, however, that in our experiments, the CSP-filtered EEG signals cannot be considered a particularly complex type of data, as the output of each filter is averaged over time, producing just one value (average power) per output CSP channel. In this context, application of the MLP may be seen as a method of comparison and verification of whether the simpler (and faster) LDA is sufficient to perform successful classification in the considered motor imagery task recognition problem.

The MLP classifier used in our experiments was configured to have n inputs in the first layer (where n is the number of CSP filters applied), 2 hidden layers containing 20 neurons each, with *ReLU* activation function and 3 neurons in the output layer (one for each class). This configuration was selected based on numerous preliminary experiments involving various neural architectures and considering i.a. their training capabilities and generalization properties.

MATERIAL

Motor imagery EEG dataset

We decided to conduct our experiments on a dataset prepared by Cho et al. (2017). This dataset contains EEG signal recordings of 52 healthy subjects performing either motor or motor imagery hand movements (of which we only used the latter ones). Each participant performed 100 or 120 trials for left/right-hand motor imagery movement and each trial lasted around 7 to 8 seconds.

Recording of a single trial begins with 2 seconds of a rest state, then for three seconds an instruction (cue) is shown on a screen, telling the subject to imagine moving left or right hand and finally the instruction disappears from the screen for another 2 seconds of a rest state followed by 0.1 to 0.8 seconds between trials. Trial timeline is shown in Fig. 4.

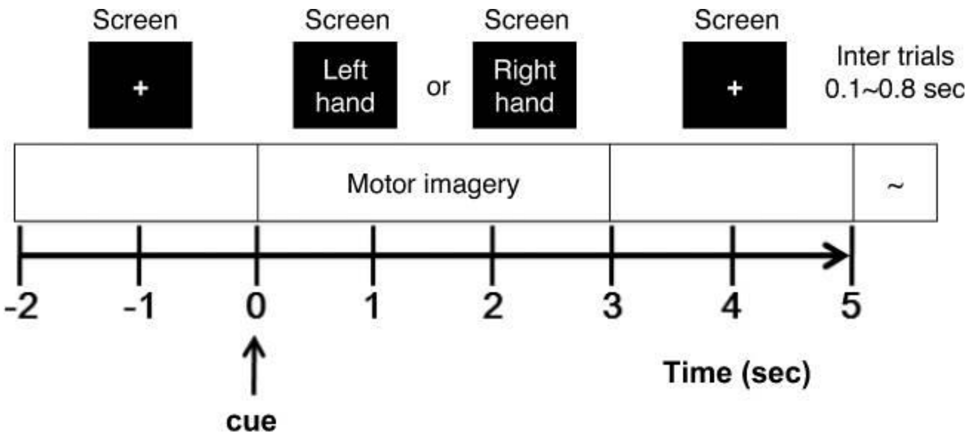

Figure 4. A single trial from the original EEG dataset (Cho, et al., 2017).

EEG signal may be distorted by a variety of artifacts. It is essential to make sure that the data used in classification experiments does not contain too much noise and the high-pass/band-pass filtering used to remove drifts and power line frequency components is just one of the necessary preprocessing steps. Moreover, information about potentially bad trials – as determined by voltage magnitude or correlated with actual muscle activity (EMG) – provided by the authors of the dataset is used. The trials marked as bad are removed from our experiments. It should be noted that it sometimes leads to an imbalance between the classes and for some of the subjects, even up to 90% of their trials are being dropped, which makes the classification task virtually impossible.

To prepare the data for the classification, some additional processing was necessary. Signal splits were extracted from a single trial and assigned an appropriate label. Each trial contains two states, as illustrated in Fig. 2: the rest state and the left/right imagery movement. The rest state split is extracted from the first 2 seconds of a trial recording. We decided not to use the 2 seconds after the imagery movement stops, as this split is likely to be corrupted by both P300 and post imagery movement lower *beta* ERS. To extract imagery movement split, we cut the trial fragment from 0.5 to 2.5 seconds after the instruction appears on the screen. The offset of 0.5s is needed to avoid P300 distortion.

The classification data obtained in this way is not balanced, naturally, as the rest class has twice as many examples as either of the imagery movement data. This imbalance may be an issue in multiclass classification, but it poses no problem in hierarchical classification because in the first classification step (binary classification of rest and imagery movement), the instances of left and right imagery movement are combined into one class.

EXPERIMENTS

Two metrics employed during the experiments were: classification accuracy and runtime. Neither of these should be considered significantly more valuable for VR applications, so in practice, the most optimal combination of accuracy score and runtime should be searched for.

The dataset, described in the previous chapter, is used in a 10-fold cross-validation scheme (train - test ratio: 80% - 20%). As mentioned before, the multiclass balanced model structure required reducing the number of the rest state examples, which was done before generating the classification data. This classification-oriented dataset was used in every experiment to assure consistency.

All the experiments were run on the same hardware: AMD Ryzen 3900X processor, Silicon Power 512GB NVMe A80 SSD drive and HyperX 2x16GB 3200MHz CL16 Fury RAM memory. Minimum background processes were running to avoid affecting runtime which was one of the metrics used in experiments.

Hierarchical binary classification vs multiclass approach

Application of the basic (2-class) CSP filters in our three-class problem, required using the hierarchical approach (first classifying the input state into rest/imagery movement, and then – if an imagery movement state was detected – it was further classified into left or right imagery hand movement). Multiclass CSP filters, however, enabled us to simplify the classification procedure.

The first group of experiments was conducted with 10 channel configuration, LDA classifier and 9-14Hz band-pass filter. The obtained results are presented in Fig. 5 (subject classification accuracy score), Table 1 (combined accuracy of each model), Table 2 (accuracy score broken down into individual classes) and Table 3 (time required for training/testing the models).

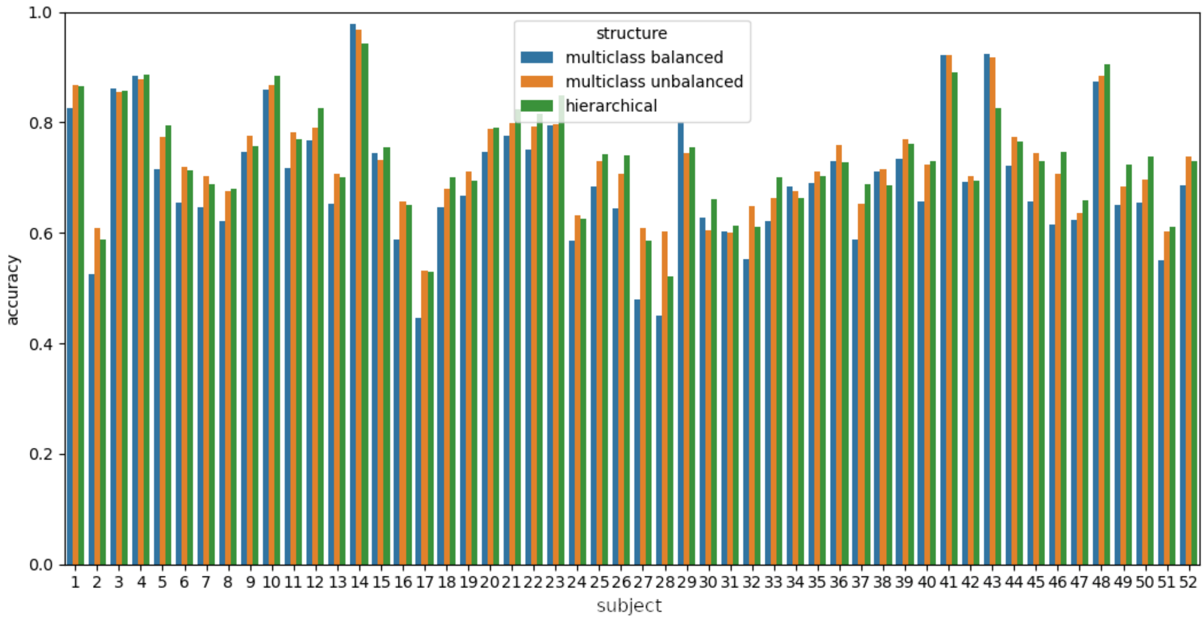

Figure 5. Subject classification accuracy for hierarchical, multiclass balanced and multiclass unbalanced model structure.

Table 1. Combined classification accuracy for hierarchical, multiclass unbalanced and multiclass balanced models.

Model	Accuracy
Hierarchical	0.7
Multiclass unbalanced	0.693
Multiclass balanced	0.687

Table 2. Classification accuracy broken down over class for hierarchical, multiclass unbalanced and multiclass balanced models.

Model	Rest accuracy	Left accuracy	Right accuracy	Left and Right accuracy
Hierarchical	0.832	0.637	0.628	0.633
Multiclass unbalanced	0.872	0.609	0.576	0.593
Multiclass balanced	0.807	0.649	0.622	0.636

Table 3. Average train and test runtime for hierarchical, multiclass unbalanced and multiclass balanced models.

Model	Train runtime	Test runtime
Hierarchical	0.405s	0.0139s
Multiclass unbalanced	0.316s	0.0073s
Multiclass balanced	0.248s	0.00563s

LDA and MLP classifiers

In the second group of experiments, two classifiers were used on top of the CSP filter-based preprocessing: LDA and a multilayer perceptron. MLP was trained using *Adam* optimizer with a constant learning rate of 0.001 and 1000 maximum iterations. This experiment was conducted on the multiclass balanced model with 10 channels and 9-14Hz band-pass filter. Subject classification accuracy score is shown in Fig. 6, combined accuracy in Table 4 and average runtime in Table 5.

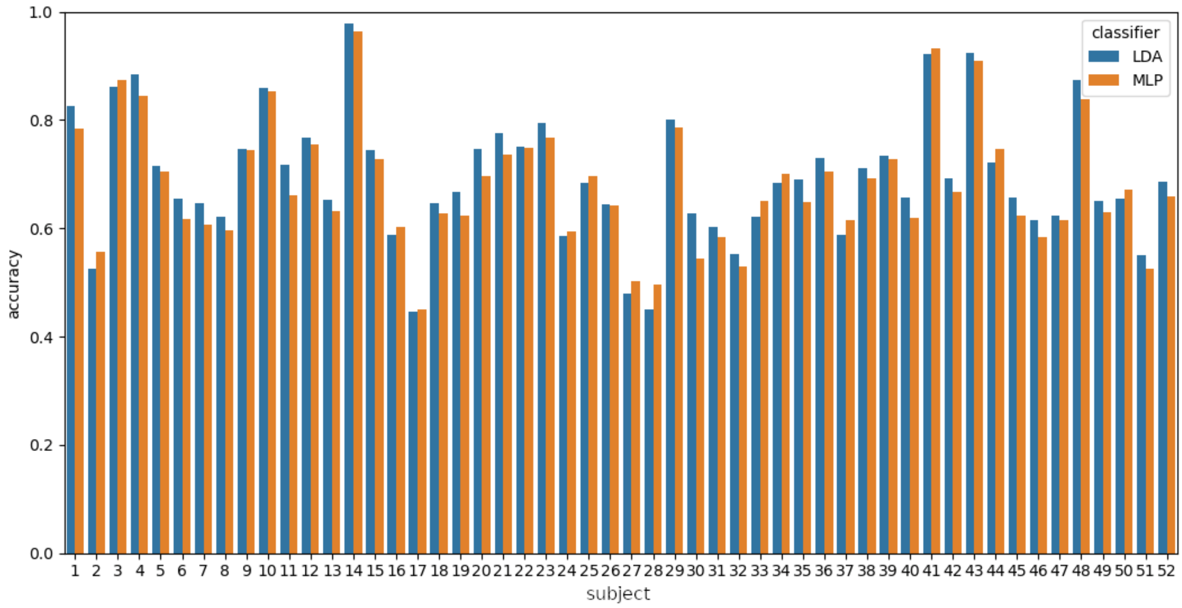

Figure 6. Subject classification accuracy comparison for LDA and MLP classifiers.

Table 4. Combined classification accuracy for LDA and MLP classifiers.

Classifier	Accuracy
LDA	0.693
MLP	0.679

Table 5. Average train and test runtime for LDA and MLP classifiers.

Classifier	Train runtime	Test runtime
LDA	0.24s	0.00599s
MLP	1.04s	0.0057s

Frequency band selection

The third group of experiments comprised classification tests with three different band-pass filters limiting the frequency range of the input EEG signal to 9-14Hz (potentially containing *mu* band ERD and ERS), 19-25Hz (potentially containing lower *beta* band ERDs and ERSs) and 6-30Hz (potentially containing both *mu* and lower *beta* ERDs and ERSs). This experiment was conducted on the multiclass balanced model with 10 channels and the LDA classifier. Accuracy classification metric was used for the evaluation of the results. No runtime experiments were performed for various band-pass filters, as there is obviously no difference in computational complexity between them. Subject classification accuracy score is shown in Fig. 7 and combined accuracy – in Table 6.

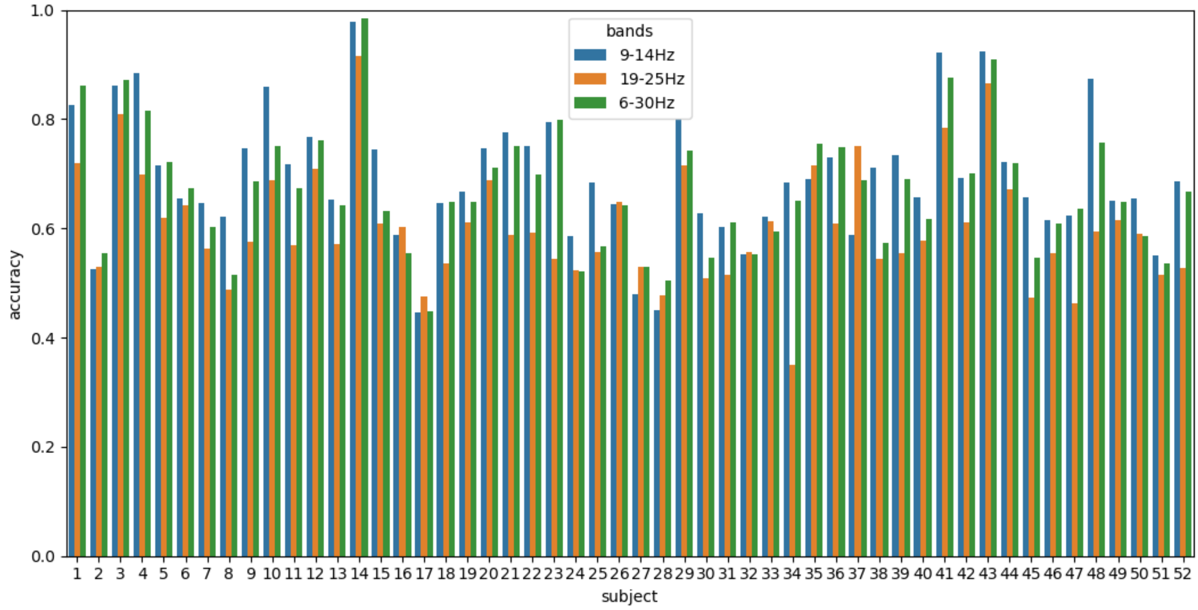

Figure 7. Subject classification accuracy comparison for 9-14Hz, 19-25Hz and 6-30Hz bands.

Table 6. Combined accuracy for 9-14Hz, 19-25Hz and 6-30Hz.

Band	Accuracy
9-14Hz	0.693
19-25Hz	0.603
6-30Hz	0.668

Channel selection

Four different channel configurations (2, 10, 18 and 64 channels) were compared in the fourth group of tests. This experiment was conducted on the multiclass balanced model with 9-14Hz band-pass filter and the LDA classifier. Subject classification accuracy score is shown in Fig. 8, combined accuracy results in Table 7 and average runtime in Table 8.

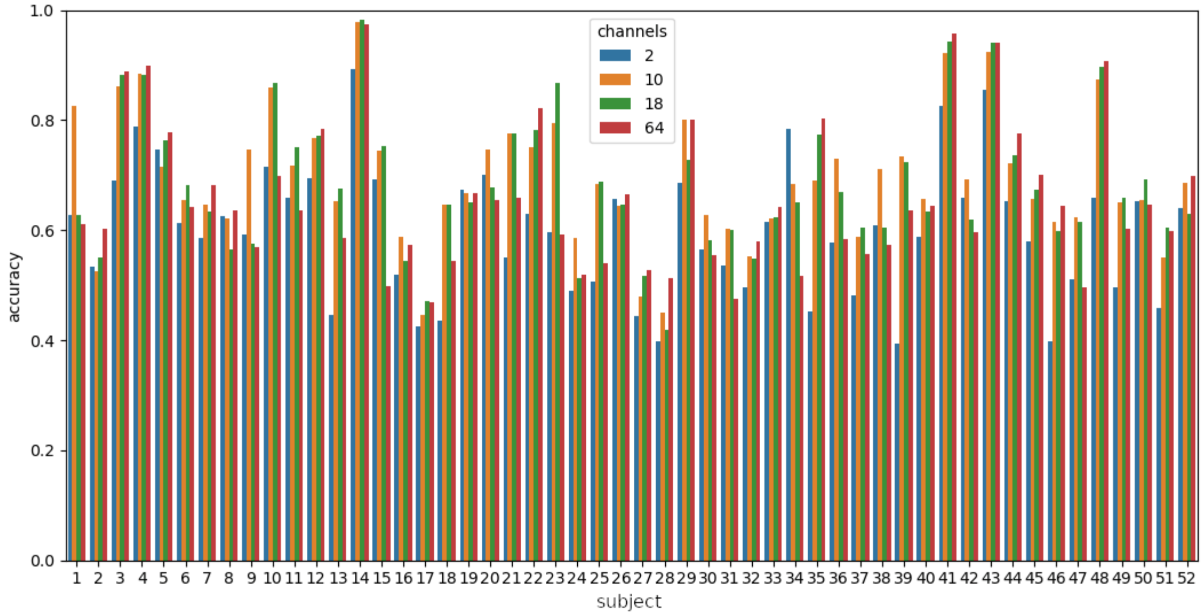

Figure 8. Subject classification accuracy for 2, 10, 18 and 64 EEG channels.

Table 7. Combined classification accuracy for 2, 10, 18 and 64 EEG channels.

Channel set (identified by channel count)	Accuracy
2	0.598
10	0.693
18	0.683
64	0.657

Table 8. Average train and test runtime for 2, 10, 18 and 64 EEG channels.

Channel set (identified by channel count)	Train runtime	Test runtime
2	0.035s	0.00135s
10	0.24s	0.00609s
18	0.501s	0.00683s
64	6.4s	0.0124s

Combined best model

To achieve the best results, the multiclass balanced model was selected. The data from 10 EEG channels was filtered with 9-14-Hz band-pass filter, preprocessed with 10 CSP filters and subjected to the classification procedure with LDA. Patient classification accuracy scores are shown in Fig. 9 and Table 9 presents the accuracy for the individual classes. Overall accuracy was 69.3%.

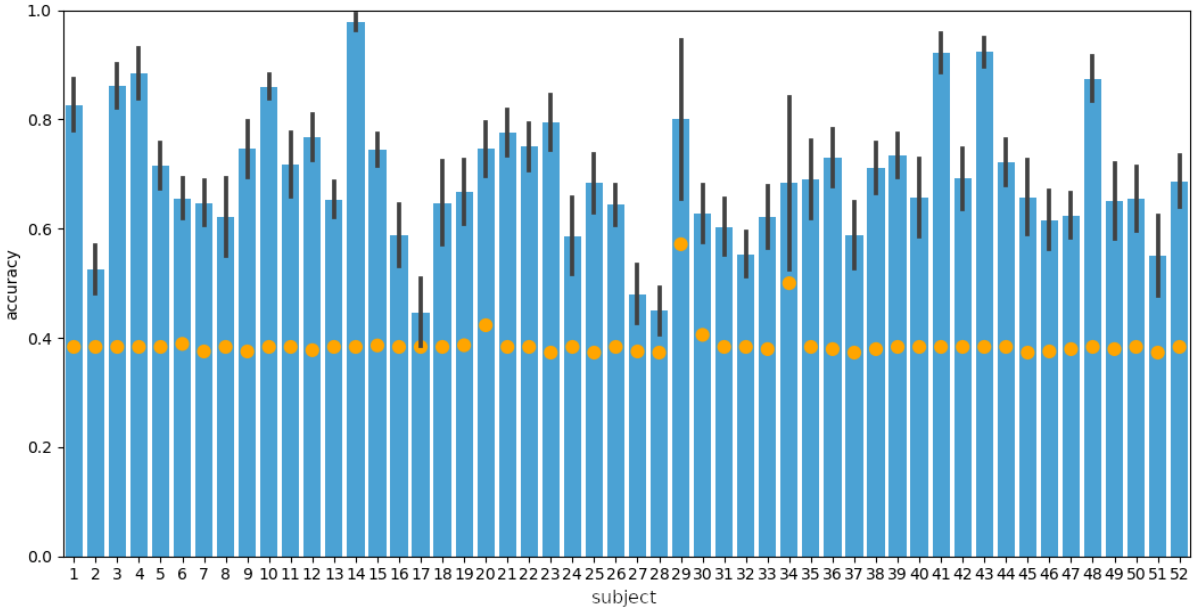

Figure 9. Subject classification accuracy for the best model. Standard deviation is presented by vertical grey bars and 5% best chance results are shown by orange dots.

Table 9. Classification accuracy with respect to the class.

Class	Accuracy
Rest state	0.807
Left-hand imagery movement	0.649120
Right-hand imagery movement	0.621750

DISCUSSION

Hierarchical and both multiclass models achieved significantly better classification accuracy scores for the rest state (83,2%, 87.22% and 80.7% respectively) than for the left/right movement (63.3%, 59.3% and 63.6% respectively). The balanced multiclass model obtained the highest accuracy on imagery movement classes (63.6%), but only slightly better than other models (63.3% and 59.3%). The balanced multiclass model was also the one that learned and produced results in the shortest time (0.248s/0.00563s vs 0.405s/0.0139s for hierarchical and 0.316s/0.0073s for multiclass unbalanced model). The implemented hierarchical model has its structure tied up to how the dataset was prepared. Using this model for another dataset with, for example, additional imagery leg movement examples, would require some significant changes.

LDA and MLP classifiers achieved similar accuracy scores (69,3% and 67.9%), proving that the simpler LDA classifier is enough for this classification task. The LDA classifier produced results in a similar time to the MLP classifier (0.00599s vs 0.0057s) but learned four times faster (0.24s vs 1.04s), which may be treated as an important advantage, especially in therapeutic scenarios involving re-training of the classifier in real-time.

Three frequency bands were selected, based on ERD/ERS characteristics typical for motor imagery events. As it turned out, the best overall accuracy score was achieved for 9-14Hz band (69.3%) followed by 6-30Hz band (66.8%) and – with noticeably worse accuracy score – 19-25Hz band (60.3%). It is worth noting, that the classification accuracy score for some of the patients (17, 26, 27, 32 and 37 in Fig. 7) was higher in lower *beta* band than in the other bands. Further improvement could be achieved by selecting even narrower frequency bands on a per-subject basis, as suggested by Rosipal, Rošťáková and Trejo (2022).

Choosing only 2 channels was not enough (only 59.8% accuracy), either due to the lack of re-referencing possibilities or failing to precisely place the electrodes exactly over the target hand movement motor cortex part. Choosing 10 and 18 channels yielded comparable classification results (69.3% vs 68.3%) and test runtime. However, twice shorter training time (0.24s vs 0.501s) made 10 channel configuration a better choice.

CONCLUSIONS

In this paper, a solution was proposed for three-class (rest, left imagery hand movement, right imagery hand movement) classification that scored 68.9% accuracy in near real-time (training in 0.248s and producing results in 0.00563s). The proposed hierarchical model, although achieving the highest overall accuracy, was slower, more complex and less accurate for left/right imagery movement classes than the multiclass model. A less complex LDA classifier achieved comparable results to a much more complicated MLP classifier while learning 4 times faster. 9-14Hz band-pass filtering yielded better accuracy than 19-25Hz and 6-30Hz bands, proving that the *mu* band is the best one to use for motor imagery task classification. Channel configurations with more than 10 electrodes increased runtime significantly and did not improve accuracy. The conducted experiments and the resulting EEG classification model configuration will serve as a strong base for future works involving BCI-based VR environment design and implementation.

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SOCIAL AND SATISFIED? SOCIAL USES OF MOBILE PHONE AND SUBJECTIVE WELLBEING IN LATER LIFE

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Abstract: *The current study examined the associations between socio-demographic background and engagement in social uses of mobile phone, and between the engagement in these uses and life satisfaction and health satisfaction in later life through the lens of digital divide and uses and gratifications theories. The data, collected from the retired Internet users (62 and older) residing in seven countries (N = 5713), were analyzed using logistic and linear regression models. The results show that education and age predicted the engagement in social uses in the most consistent way. A number of social uses positively related to both life and health satisfaction. Of the particular uses, e-mailing and instant messaging were positively associated with life and health satisfaction. The results imply that socio-demographic background predicts the engagement in social uses of mobile phone in later life, that the engagement in such uses plays an overall significant role in wellbeing in later life, and that some particular uses play a greater role than others in this regard.*

Keywords: *digital divide, mobile phone, older adults, social use, subjective wellbeing, uses and gratifications.*

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INTRODUCTION

Information and communication technologies (ICTs) continue to affect people of all ages, though in an unequal manner (Berner et al., 2015; Quan-Haase et al., 2018). Older adults constitute a constantly growing segment of mobile technology users (Rosales & Fernandez-Ardèvol, 2016). Mobile technology offers older adults numerous opportunities to improve the quality of their lives, ranging from better self-monitoring of health to the facilitated maintaining of social relations and psychological wellbeing (Chiu et al., 2016). Although older adults hold generally positive attitudes towards mobile technologies (Neves & Amaro, 2012) and many of them have already incorporated these technologies into their lives (Fernandez-Ardèvol & Ivan, 2013), there is relatively little evidence regarding the relationship between mobile phone uses and wellbeing in later life.

The goal of this study was to explore two types of associations: (a) between socio-demographic background and social uses of mobile phone, and (b) between social uses of mobile phone and two subjective wellbeing measures (life satisfaction and health satisfaction) in later life. These associations were examined in the cross-sectional international sample of older Internet users. In this study, *social uses of mobile phone* are defined as uses of mobile phones "for social purposes, such as social networking, messaging, phone calls and maintaining social relationships." (Elhai et al., 2017, p.76). Two theoretical frameworks, the digital divide theory and the uses and gratifications (U&G) theory, were applied to guide the research and facilitate the interpretation of results.

The rationale behind investigating engagement in social uses of mobile phone and subjective wellbeing in later life is rooted in three issues. First, among all possible types of mobile phone usage, social uses are expected to be the most *beneficial* for older adults. Links with close family members become more significant as people age (Sims et al., 2017), while the number of their distant social ties tends to decrease over the years (Petrovčič et al., 2015). Older adults are therefore more likely to experience loneliness and social isolation than their younger counterparts (Xie et al., 2020), the fact that may lead to serious mental disorders, cognitive disparities, and even mortality (Courtlin & Knapp, 2017). Feelings of loneliness and social isolation may be even more strongly emphasized in the retired older adults, many of whom experience detachment from social circles developed and maintained during their participation in the labor market (Cotten et al., 2013). Social uses of mobile phone may therefore mitigate the impact of these consequences of aging, as well as improve wellbeing and satisfaction with various domains of life (Delello & McWhorter, 2017; Sims et al., 2017).

Second, prior research on ICT use and wellbeing in later life have yielded *inconsistent results*. Some of these studies found that ICT use positively relates to wellbeing, quality of life, and health (Heo et al., 2015; Kim et al., 2020; Sims et al., 2017), contributes to greater social connectivity, support, and inclusion (Chiu et al. 2016), and to greater life satisfaction (Kim & Shen, 2020). Other studies found little or no association between ICT use and life/wellbeing outcomes (e.g., Cotten et al., 2013; Francis et al., 2019).

Third, the *design* of the current study has several advantages compared with the previous studies on the alike topics (Chiu et al., 2016; Petersen et al., 2016; Seifert & Schelling, 2015; Vicente & Lopez, 2016). Despite their insightfulness, earlier qualitative study designs (e.g., Ivan & Fernandez-Ardèvol, 2017; Vicente & Lopez, 2016) did not allow establishing a systematic structure of predictors and outcomes of mobile phone use in later life. For the most part, previous quantitative studies did not examine the association between each separate use and wellbeing outcomes (e.g., see Elhai et al., 2017; Seifert & Schelling, 2015), but rather focused on the relationship between the overall usage or mobile ownership and wellbeing measures. This approach disregards the notion that some ICT uses may relate to subjective wellbeing to a greater extent than others. Lastly, prior studies were based on relatively small samples, usually from a single country (Chiu et al., 2016; Petersen et al., 2016; Vicente & Lopez, 2016). In contrast, the current study applies quantitative methodology to a large data set collected from seven countries and examines overall social mobile phone usage as well as the engagement in particular social uses.

The results of the study have a potential to assist communities and public officials in their efforts to mitigate the undesired effects of aging through mobile technology. The COVID-19 pandemic, when older adults around the world are staying at home more than ever following governments' restrictions and safety measures (Nimrod, 2020b; Seifert et al., 2021), could have exacerbate these effects. The limited possibilities to maintain offline social relationships could have negatively impacted their subjective wellbeing.

As previously mentioned, the current study uses two theories to explain the studied associations. First, the association between socio-demographic background and engagement in social uses of mobile phone was examined through the lens of the digital divide perspective (Yu et al., 2016). Second, the association between social mobile phone uses and wellbeing outcomes was examined through the lens of the U&G theory (Han et al., 2015; Heravi et al., 2018). These two frameworks are used as neither can fully explain the studied associations. The role of socio-demographics in predicting ICT use can be better explained through the lens of the digital divide theory, which does not seek to understand users' needs in their ICT use. In contrast, in the U&G framework, needs or motivations are used to explain ICT use or its relation to various aspects of life, while the role of socio-demographic background is generally overlooked.

In sum, this study intends to respond to the following research questions. The first two questions will address the digital divide perspective:

RQ1: Which socio-demographic characteristics are associated with number of social uses of mobile phone in later life?

RQ2: Which socio-demographic characteristics are associated with the engagement in particular social uses of mobile phone in later life?

The two additional research questions will address the U&G theory:

RQ3: Does the number of social uses of mobile phone positively relate to subjective wellbeing in later life?

RQ4: Engagement in which particular social uses of mobile phone is associated with greater subjective wellbeing in later life?

In this cross-sectional study, we chose to examine how the social uses of mobile phone are associated with wellbeing measures. We acknowledge that the relationship can also be the opposite; greater subjective wellbeing can motivate people to use more social functionalities of their mobile phones. However, we follow the literature which examines more the former type of associations (Cotten et al., 2013; Elhai et al., 2017; Francis et al., 2019; Heo et al., 2015; Ihm & Hsieh, 2015; Kim et al., 2020; Petersen et al., 2016; Sims et al., 2017). In order to properly examine the opposite associations, more information about the motivations and expected gratifications would be needed. The survey data used in the current study does not contain such information.

LITERATURE REVIEW

Digital divide theory and older adults' ICT use

The digital divide was one of the first theoretical concepts used in digital media and communication studies to refer to various types of inequalities in the ICT adoption/use domain. The literature in this domain distinguishes between first-level, second-level, and third-level digital divide. When the Internet was in its infancy, the (first level) digital divide referred to differences between having and not having access to computers and/or the Internet. As Internet penetration reached a saturation point in most countries of the world, meaning that the "use-nonuse" gap has substantially narrowed, research began attempting to understand the *second-level divide* (Mesch, 2016). It is defined as inequality in ICT uses (Chopik et al., 2017; Hargittai et al., 2019) or in digital skills (Quan-Haase et al., 2018). More recently, the concept of the *third-level digital divide*, which refers to inequalities in the beneficial outcomes (e.g., learning, productivity, wellbeing, and quality of life) of ICT use (Scheerder et al., 2017), has been introduced. It maintains that individuals do not benefit equally from ICT use even when they are equally likely to access and use it (Van Deursen & Helsper, 2015).

As older adults constitute a highly heterogeneous group in terms of ICT adoption and use (Hargittai et al., 2019; Hänninen et al., 2020), the digital divide appears to manifest itself in the older population in particular ways (Friemel, 2016). For example, older age was found associating with lower number of ICTs used (Chopik et al., 2017). With respect to gender, women value cooperation (Merchant, 2012) and are more motivated than men to maintain their social ties (Yu et al., 2016). A higher level of education reflects better ICT skills (Hargittai & Dobransky, 2017), and a higher income reflects greater ability to make financial expenditures (König et al., 2018). As to marital status, married people tend to be more motivated towards ICT use because their life partners are likely to encourage them to use the technology (Chang et al., 2015) and to provide an assistance with use-related problems when necessary (Berner et al., 2015). As to locality, urban localities have a more developed ICT infrastructure (König et al., 2018) and a larger supply of retail outlets (Dennis et al., 2016) where ICT services and products, including mobile phones, can be purchased.

Based on these findings from the previous research, it is expected that women and younger respondents will be more likely to engage in social uses of mobile phone than men and older respondents, respectively. Similarly, it is assumed that respondents with bachelor, master or doctoral degrees (hereinafter: tertiary education) and those with incomes higher than their country's average (hereinafter: high income) engage more in social uses of mobile phone than respondents with post-secondary or lower level of education (hereinafter: non-tertiary education) and those with an average or lower than average incomes (hereinafter: mean or lower income). Also, married individuals are assumed to engage more in social uses of mobile phone compared to unmarried (meaning single, divorced or widowed). Finally, respondents residing in large urban (i.e., big cities) and small urban (i.e., the suburbs of big cities, towns or small cities) localities are expected to undertake social use of mobile phone more than those living in rural (i.e., country villages or farms/homes in the countryside) localities.

Uses and Gratifications theory and older ICT users

According to the U&G theory, individuals' selection of media is purposive and conscious (Han et al., 2015) since people are motivated to use media for gratification of the particular individual needs (Heravi et al., 2018). Since the choice of media is based on past gratifications (Bondad-Brown et al., 2012), the media selected for consumption are those perceived (and known) to be able to meet consumers' needs and desires (Vaterlaus, 2017). Despite a number of methodological criticisms (see Alhabash & Ma, 2017), U&G theory has been widely used to study the antecedents and outcomes of communication due to its high applicability (Chung & Kim, 2008). It focuses not only on motives for media use but also on the results of their use (Park & Goering, 2016), therefore being relevant for the current study.

Older adults' use of ICT is likely to be performed when technology does gratify or is expected to gratify their needs (Chang et al., 2015; Francis et al., 2018). This is also true for mobile phone usage, which is typically more utilitarian than hedonistic in older adulthood (Fernandez-Ardèvol & Ivan, 2013). One explanation to this can be found in the socio-emotional selectivity theory. According to it, because the older adults' future life perspective is shorter that of younger age cohorts, they tend to prioritize emotionally meaningful activities and gratify their short-term needs (Kim & Shen, 2020). Additional explanation to utilitarian approach in ICT use by older adults refers to the limitations of the later life. Geographical barriers (Francis et al., 2018), potential loss of social contacts (Cotten et al., 2013), and deteriorating health (Mesch, 2016) are major concerns in this life stage. Social uses of mobile phone are designed to help older adults to overcome these concerns and, consequently, improve their wellbeing. Therefore, it is expected that social uses of mobile phone will be associated with greater subjective wellbeing in later life.

Since numerous activities are included in ICT use, the contribution of each of them to wellbeing may differ (Nimrod, 2020a), as these activities may provide varying benefits and gratify different needs. For example, instant messaging can gratify health-related needs and therefore provide solutions for maintenance or improvement of health status. In contrast, social networking sites via mobile phone can be used to gratify needs for social entertainment and unwinding and therefore provide solutions for a more efficient spending of time. Therefore, the current study has adopted the toolkit approach (Smock et al., 2011), according to which each media outlet should not be seen as a single entity but rather as a combination of numerous features which may be differently used and provide varying gratifications. Hence, we will also examine whether and how each particular social use of mobile phone is associated with greater subjective wellbeing in later life.

METHODS

Data

The data used in the current study were attained from the 2018 wave of the Ageing, Communication, Technologies (ACT) cross-national longitudinal survey conducted among internet users aged 62 and over from Austria, Canada, Finland, Israel, the Netherlands, Romania, and Spain[i]. The overall aim of the survey was to study older audience in the digital media environment. Data were collected online in six of the countries, using commercial online respondent panels. Only in Romania they were collected by telephone due to the relatively low share of Internet users in the country's older population (Ivan & Schiau, 2018). The samples were representative of the older population of Internet users in each country as age and gender quotas were used in the sampling (Loos et al., 2019).

Sample

The population of the current study consisted of retired older Internet users for two reasons. First, differences in (social) uses of mobile phone can be attributed to the variations in amount of available free time, which is contingent upon the occupational status (Näsi et al., 2012). Second, affordances for purchasing, accessing and using technology may vary according to employment status (Hargittai & Dobransky, 2017) as people of various occupational statuses may have different financial abilities and digital skills.

In total, 7940 older Internet users provided their responses in the current wave of the survey. Filtering out the responses of those who reported their occupational status other than retired resulted in elimination of 1702 entries from the database. Of the remained 6238 responses, 447 had missing data for variables that referred to social uses of mobile phone. Another five respondents indicated they did not use mobile phone, so their answers were also discarded. Responses of another 62 participants, who reported their ages as 60 or 61, as well as 11 cases of missing data for age, were also excluded. Therefore, study's analytical sample included the responses of 5713 retired Internet users.

Measurement

The data were collected using a previously validated questionnaire (Jensen & Helles, 2015), with validated translations into Dutch, French, German, Hebrew, Romanian and Spanish available from the previous wave. As Finland joined the project on the current wave, first translation to Finnish language was performed by local research team. A back translation to English was carried out by an independent proofreader, and the process was reiterated until the Finnish version was consistent with the original questionnaire (Loos et al., 2019).

Measures

Subjective wellbeing

Life satisfaction is an ordinal variable measured with the question "Thinking about your own life and personal circumstances, how satisfied are you with your life as a whole?". The responses ranged from "1" (completely dissatisfied) to "10" (completely satisfied).

Health satisfaction is an ordinal variable measured with the question "Thinking about your physical health, how satisfied are you with your health as a whole?". The responses here also ranged from "1" (completely dissatisfied) to "10" (completely satisfied).

Social uses of mobile phone

Number of social uses of mobile phone (*full scale*) was constructed based on the functions listed in the following item: "Which functions do you use on your mobile phone?". The list of 19 functions was presented to respondents, and they had to check all that applied to them. Each function was then recoded into a binary variable ("1" – used, and "0" – not used). The calculated scale was therefore defined as the sum of responses regarding six functionalities which match to the abovementioned definition of social uses provided by Elhai et al. (2017). These items were: voice calling, using short message services (SMS), using multimedia message services (MMS), using social networking sites (SNS), e-mailing, and instant messaging. A higher score on the scale, ranging from zero to six, reflects a greater number of social uses of mobile phone. Since this variable represents variety/diversity and not intensity of these uses, no conclusions with respect to frequency of use should be made (this issue will be addressed in Limitations).

Number of social uses of mobile phone (*short scale*). The scale was computed for purposes of sensitivity analysis using as same scheme as in construction of the previous variable. Since voice calling and sending/receiving SMS are two basic functions on any phone, and actually are the two most frequently mentioned uses by older adults (Choudrie et al., 2017; Fernandez-Ardèvol & Ivan, 2013), they were not included in this scale. Therefore, the score on it ranged from zero to four. By comparing the results that are based on the full and those based on the short, scale, the relative importance of basic voice calling and using SMS for older Internet users' satisfaction with life and with health is assessed.

Particular social uses of mobile phone. The six abovementioned social uses were also treated as separate binary variables. In each variable, respondents who did not engage in each particular use represented the reference category.

Socio-demographic variables

Gender was defined as a dichotomous variable, with female respondents as the reference category. *Age* was measured continuously in years. *Level of education* was measured as a dichotomous variable, with respondents having a non-tertiary education as the reference category. *Income level* was measured dichotomously, with respondents who reported having mean or lower income as the reference category. *Marital status* was defined a dichotomous variable, with unmarried respondents as the reference category. *Type of residential locality* was defined by two dummy variables—large urban and small urban localities. Residents of rural localities represented the reference category.

Statistical analysis

Data were analyzed using SPSS v.23 software. In terms of statistical methods, linear regression models were applied to explore the associations between socio-demographic background variables and number of social uses of mobile phone. Then, logistic regression analysis was employed to estimate the likelihood of engaging in each of the six social mobile phone uses. Lastly, linear regression modelling was applied to examine the relationship between number of social uses of mobile phone, as well as between each use separately, and each subjective wellbeing outcome, while controlling for background variables. In every regression model, all variables were included in a single step (the enter model). Each model controlled for country of residence (Israel as the reference category).

RESULTS

Descriptive results

Descriptive statistics for each of the variable included in regression models are presented in Table 1.

Table 1. Sample characteristics**.**

Variable *Categories*	***n***	***% or M***	***SD***
Gender			
Male	3030	53.0	
Female	2683	47.0	
Age *(62-95)*	5713	69.95	5.7
Education			
Tertiary	1998	35.2	
Not-tertiary	3673	64.8	
Income			
Higher than mean	2202	44.7	
About the mean or lower	2720	55.3	
Marital status			
Married	3974	70.1	
Unmarried	1695	29.9	
Locality			
Large urban	1831	32.2	
Small urban	2733	48.0	
Rural	1124	19.8	
Life satisfaction *(1-10)*	5670	7.8	1.7
Health satisfaction *(1-10)*	5681	7.1	1.9
Number of social uses of mobile phone (full scale) *(0-6)*	5713	3.2	1.6
Number of social uses of mobile phone (short scale) *(0-4)*	5713	1.7	1.3

Note. M = Mean; n = Number of cases in each category; SD = Standard Deviation.

The participants' age ranged from 62 to 95 (*M* = 69.95; *SD* = 5.7). Of them, 53% were men and 70.1% were married. As to education and income, 35.2% reported having a tertiary education, and about 44.7% reported high income. As to locality of residence, 32.2% reported residing in large urban localities, 48% in small urban localities, and the rest 19.8% in rural localities. The respondents demonstrated a relatively high mean level of satisfaction with their lives (*M* = 7.8; *SD* = 1.7) and a moderately high mean level of satisfaction with their health (*M* = 7.1; *SD* = 1.9). On average, respondents reported performing about 3.2 social uses of mobile phone (*SD* = 1.6).

Figure 1 shows the distribution of respondents' mobile phone uses weighted by country. Frequencies of non-social uses are shown for comparison purposes only.

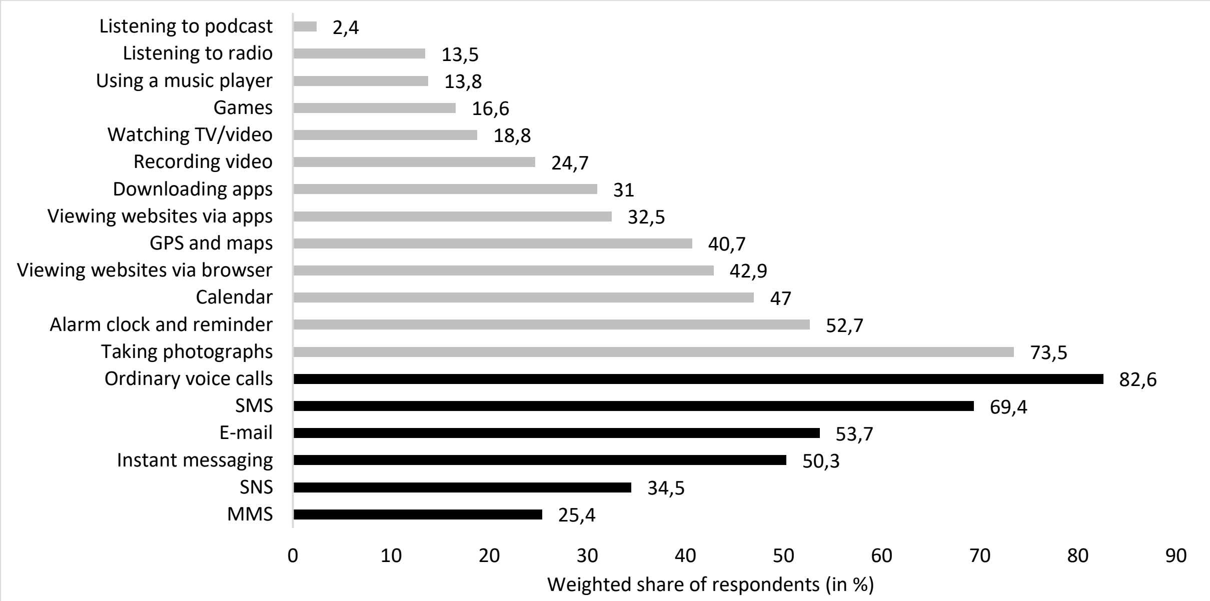

Figure 1. Distribution (in percentages) of social (in black) and other (in grey) mobile phone uses.
Note. Actual N = 5713; Weighted N = 3073.
GPS = Global Positioning System; MMS = Multimedia Message Service; SMS = Short Message Service; SNS = Social Networking Sites.

As expected, making voice calls (82.6%) and using SMS (69.4%) were the most frequent mobile social uses, corresponding to the similar finding by Choudrie et al. (2017), followed by e-mailing (53.7%), instant messaging (50.3%), and using SNS (34.5%). This sequence of uses corresponds to the sequence found by Barbosa Neves et al. (2018) regarding the internet use among the older population. The least common social use, sending MMS, was performed by about 25.4% of the respondents.

Predicting social uses of mobile phone

Table 2 shows the results of the analysis predicting the number of social uses of mobile phone by socio-demographic background.

The results suggest that male respondents engaged in fewer social uses than female respondents. Age was found to be negatively associated with number of social uses. Respondents with a tertiary education and a high income engaged in more social uses than respondents with non-tertiary levels of education and with mean or lower income, respectively. Married respondents engaged in more social uses than unmarried. Finally, respondents residing in large urban localities engaged in more social uses of mobile phone than respondents living in rural localities, while no difference appeared in this regard between the latter and respondents residing in small urban localities.

Table 2. OLS regression analyses - number of social uses of mobile phone by socio-demographic background (n = 4857).

	Number of social uses (full scale) b (SE)	***Number of social uses (short scale, without calls and SMS)*** b (SE)
Constant	7.08***	4.63***
Female (ref.)		
Male	-.12* (.05)	-.11** (.04)
Age (in years)	-.05*** (.004)	-.04*** (.003)
Non-tertiary education (ref.)		
Tertiary education	.22*** (.05)	.14*** (.04)
Mean or low income (ref.)		
High income	.29*** (.05)	.21*** (.04)
Unmarried (ref.)		
Married	.10* (.05)	.11* (.04)
Rural (ref.)		
Large urban	.15* (.06)	.14** (.05)
Small urban	.08 (.06)	.09 (.05)
Israel (ref.)		
Austria	-.55*** (.10)	-.59*** (.08)
Canada	-1.56*** (.10)	-1.20*** (.08)
Finland	-.30** (.10)	-.30*** (.08)
Netherlands	-.98*** (.12)	-.66*** (.10)
Romania	-2.07*** (.11)	-1.47*** (.09)
Spain	-.71*** (.10)	-.17* (.08)
F	83.35***	72.93***
R^2	.183	.164

Note. OLS = Ordinary Least Squares; SMS = Short Message Services; b = Unstandardized regression coefficient; F = Fisher's F ratio; R^2 = Coefficient of determination (non-adjusted); SE = Standard Error.
* $p < .05$ ** $p < .01$ *** $p < .001$.

Table 3 shows the results of the logistic regression analysis predicting engagement in each one of the six social uses of mobile phone investigated in the current study by socio-demographic background. Except for the model examining the use of SMS, which exhibited a poor fit to the data, each model was both significant at the 0.001 level and fitted the data well. Therefore, only their results are shown in the table.

As Table 3 shows, the most consistent predictors were age and education. Age was found to be negatively associated with engagement in each social use. Respondents with a tertiary education were found to be more likely than respondents with non-tertiary education to engage in each of the social uses except for the use of SNS.

Other variables exhibited less consistent associations. As to gender, men were found to be less likely than women to engage in instant messaging, use of SNS and of MMS. Respondents with high income were more likely than respondents with lower income levels to use e-mail, MMS, and engage in instant messaging. Married respondents were more likely than unmarried to use e-mail and engage in instant messaging. Finally, residents of large urban localities were more likely to use e-mail and MMS via mobile phone than residents of rural localities. No difference whatsoever emerged between the latter and residents of small urban localities.

Table 3. Binary logistic analyses - likelihood of engagement in the particular social uses of mobile phone by socio-demographic background (n = 4857).

Predictors	***Voice calls***		***E-mail***		***Instant messaging***		***SNS***		***MMS***	
	OR	p	OR	p	OR	p	OR	p	OR	p
Constant	50.09	.000	31.33	.000	92.23	.000	34.04	.000	5.44	.000
Female (ref)										
Male	1.09	.340	1.02	.806	**.82**	**.006**	**.83**	**.006**	**.84**	**.019**
Age (in years)	**.99**	**.045**	**.96**	**.000**	**.94**	**.000**	**.95**	**.000**	**.96**	**.000**
Non-tertiary (ref.)										
Tertiary education	**1.26**	**.008**	**1.27**	**.001**	**1.33**	**.000**	1.03	.682	**1.19**	**.020**
Mean or lower income (ref.)										
High income	1.14	.131	**1.46**	**.000**	**1.41**	**.000**	1.07	.322	**1.31**	**.000**
Unmarried (ref.)										
Married	.91	.275	**1.18**	**.016**	**1.18**	**.028**	1.10	.172	1.10	.247
Rural (ref.)										
Small urban	.95	.658	1.09	.292	1.12	.183	1.08	.381	1.17	.091
Large urban	.98	.882	**1.32**	**.002**	1.19	.073	1.03	.750	**1.27**	**.017**
Israel (ref.)										
Austria	.62	.112	**.63**	**.001**	**.52**	**.000**	**.28**	**.000**	.80	.112
Canada	**.16**	**.000**	**.34**	**.000**	**.09**	**.000**	**.33**	**.000**	**.42**	**.000**
Finland	**.27**	**.000**	**.63**	**.001**	**.48**	**.000**	**.43**	**.000**	**2.09**	**.000**
Netherlands	.59	.122	**.69**	**.030**	**.65**	**.011**	**.44**	**.000**	**.13**	**.000**
Romania	**.08**	**.000**	**.12**	**.000**	**.14**	**.000**	**.29**	**.000**	**.19**	**.000**
Spain	**.18**	**.000**	.93	.625	**2.05**	**.000**	**.74**	**.030**	**.34**	**.000**
Model chi-square	288.31	.000	518.53	.000	1191.30	.000	254.10	.000	649.40	.000
-2 log likelihood	4169.57		6170.11		5537.61		5941.40		5116.29	
R^2	.096		.135		.290		.071		.180	

Note. MMS = Multimedia Message Service, SNS = Social Networking Sites; OR = Odds Ratio; P = Significance level; R^2 = Coefficient of determination (Nagelkerke).

Predicting life satisfaction

Table 4 shows the results of the linear regression analyses of life satisfaction by number of social uses of mobile phone.

As expected, the results show that the number of social uses of mobile phone was positively associated with life satisfaction. This association was more pronounced in the model with the short scale than in the model with the full one.

Regarding the associations of the other variables, men and residents of large urban and of small urban localities were found to be less satisfied with life than women and residents of rural localities, respectively. In contrast, respondents who reported being married, having a tertiary education, and a high income were found to be more satisfied with life than respondents who were unmarried, had non-tertiary education, and a mean or lower income, respectively. Finally, age was found to be positively associated with life satisfaction.

Table 4. OLS analysis of life satisfaction by number of social uses of mobile phone (n = 4833).

Predictors	***Model 1*** b (SE)	***Model 2*** b (SE)
Constant	5.28***	5.41***
Number of social uses (full scale)	**.08*** (.02)**	---------------
Number of social uses (short scale)	---------------	**.10*** (.02)**
Female (ref.)		
Male	-.15** (.05)	-.15** (.05)
Age (in years)	.03*** (.004)	.03*** (.004)
Non-tertiary education (ref.)		
Tertiary education	.11* (.05)	.12* (.05)
Mean or lower income (ref.)		
High income	.45*** (.05)	.46*** (.05)
Unmarried (ref.)		
Married	.44*** (.06)	.44*** (.06)
Rural (ref.)		
Small urban	-.13* (.07)	-.13* (.07)
Large urban	-.20** (.07)	-.20** (.07)
Israel (ref.)		
Austria	.27* (.11)	.28* (.11)
Canada	.10 (.11)	.09 (.11)
Finland	.22* (.11)	.23* (.11)
Netherlands	.25 (.13)	.23 (.13)
Romania	.05 (.13)	.02 (.13)
Spain	.04 (.12)	-.004 (.12)
F	18.19***	18.06***
R^2	.050	.050

Note. OLS = Ordinary Least Squares; b = Unstandardized regression coefficient; F = Fisher's F ratio; R^2 = Coefficient of determination (non-adjusted); SE = Standard Error
* *p* < .05 ** *p* < .01 *** *p* < .001.

Table 5 shows the results of linear regression analyses predicting life satisfaction by engagement in each social use of mobile phone while controlling for the socio-demographic background.

Table 5. OLS analyses of life satisfaction by engagement in particular social uses of mobile phone – each one (Models 1-6) and altogether (Models 7-8) (n = 4833).

	Model 1 b (SE)	***Model 2*** b (SE)	***Model 3*** b (SE)	***Model 4*** b (SE)	***Model 5*** b (SE)	***Model 6*** b (SE)	***Model 7*** b (SE)	***Model 8*** b (SE)
Constant	5.84***	5.58***	5.61***	5.50***	5.71***	5.75***	5.26***	5.38***
Phone calls	.02 (.07)	---------	---------	---------	---------	---------	-.03 (.07)	---------
SMS	---------	**.20** (.06)**	---------	---------	---------	---------	**.14* (.06)**	---------
E-mails	---------	---------	**.19*** (.05)**	---------	---------	---------	.10 (.06)	**.12* (.06)**
Instant messaging	---------	---------	---------	**.26*** (.06)**	---------	---------	**.20** (.06)**	**.20** (.06)**
SNS	---------	---------	---------	---------	**.12* (.05)**	---------	-.01 (.06)	-.004 (.06)
MMS	---------	---------	---------	---------	---------	**.15* (.06)**	.05 (.06)	.07 (.06)
Female (ref.)								
Male	-.16** (.05)	-.16** (.05)	-.16** (.05)	-.15** (.05)	-.16** (.05)	-.16** (.05)	-.15** (.05)	-.15** (.05)
Age	.02*** (.004)	.02*** (.004)	.02*** (.004)	.02*** (.004)	.02*** (.004)	.02*** (.004)	.03*** (.004)	.03*** (.004)
Non-tertiary education (ref.)								
Tertiary education	.13* (.05)	.12* (.05)	.12* (.05)	.12* (.05)	.13* (.05)	.13* (.05)	11* (.05)	.11* (.05)
Mean or lower income (ref.)								
High income	.48*** (.05)	.47*** (.05)	.46*** (.05)	.46*** (.05)	.48*** (.05)	.47*** (.05)	.45*** (.05)	.45*** (.05)
Unmarried (ref.)								
Married	.45*** (.06)	.44*** (.06)	.44*** (.06)	.44*** (.06)	.44*** (.06)	.45*** (.06)	.43*** (.06)	.44*** (.06)
Rural (ref.)								
Small urban	-.12 (.07)	-.13 (.07)	-.13 (.07)	-.13* (.07)	-.13 (.07)	-.13 (.07)	-.13* (.07)	-.13* (.07)
Large urban	-.19** (.07)	-.19** (.07)	-.20** (.07)	-.20** (.07)	-.19** (.07)	-.20** (.07)	-.21** (.07)	-.21** (.07)
Israel (ref.)								
Austria	.22 (.11)	.21 (.11)	.24* (.11)	.26* (.11)	.26* (.11)	.23* (.11)	.25* (.11)	.27* (.11)
Canada	-.02 (.11)	.01 (.11)	.02 (.11)	.11 (.11)	.003 (.11)	-.002 (.11)	.13 (.11)	.12 (.11)
Finland	.20 (.11)	.18 (.11)	.22* (.11)	.24* (.11)	.22* (.11)	.17 (.11)	.21 (.11)	.23* (.11)
Netherlands	.17 (.13)	.23 (.14)	.18 (.13)	.20 (.13)	.19 (.13)	.21 (.14)	.25 (.14)	.22 (.14)
Romania	-.12 (.13)	-.07 (.13)	-.03 (.13)	-.01 (.13)	-.09 (.13)	-.08 (.13)	.06 (.13)	.04 (.13)
Spain	-.02 (.12)	.06 (.12)	-.02 (.12)	-.05 (.12)	-.01 (.12)	.01 (.12)	.02 (.12)	-.03 (.12)
F	16.27***	17.16***	17.31***	17.94***	16.66***	16.77***	13.88***	15.19***
R^2	.045	.047	.048	.050	.046	.046	.052	.051

Note. MMS = Multimedia Message Services, OLS = Ordinary Least Squares, SMS = Short Message Services, SNS = Social Networking Sites; b = Unstandardized regression coefficient; F = Fisher's F ratio; R^2 = Coefficient of determination (non-adjusted); SE = Standard Error
* $p < .05$ ** $p < .01$ *** $p < .001$.

Except for making phone calls, engagement in each social use was positively associated with life satisfaction. Nevertheless, when the use variables were inserted into one model, the situation somewhat changed. Only use of SMS (in Model 7), e-mailing (in Model 8), and instant messaging (in Model 7 and Model 8) were associated with the increased levels of life satisfaction.

Predicting health satisfaction

Table 6 shows the results of the linear regression analysis predicting health satisfaction by number of social mobile phone uses.

Table 6. OLS analysis of health satisfaction by number of social uses of mobile phone (n = 4839).

	Model 1 b (SE)	***Model 2*** b (SE)
Constant	5.96***	5.97***
Number of social uses (full scale)	**.07*** (.02)**	---------
Number of social uses (short scale)	---------	**.11*** (.02)**
Female (ref.)		
Male	-.20** (.06)	-.20** (.06)
Age (in years)	.01 (.01)	.01 (.01)
Non-tertiary education (ref.)		
Tertiary education	.11 (.06)	.11 (.06)
Mean or lower income (ref.)		
High income	.44*** (.06)	.43*** (.06)
Unmarried (ref.)		
Married	.32*** (.06)	.32*** (.06)
Rural (ref.)		
Small urban	-.13 (.07)	-.13 (.07)
Large urban	-.18* (.08)	-.18* (.08)
Israel (ref.)		
Austria	.44*** (.13)	.47*** (.13)
Canada	.17 (.13)	.19 (.13)
Finland	.30* (.13)	.31* (.13)
Netherlands	.32* (.15)	.33* (.15)
Romania	.35* (.15)	.36* (.15)
Spain	.30* (.13)	.27* (.13)
F	9.48***	10.06***
R^2	.027	.028

Note. OLS = Ordinary Least Squares; b = Unstandardized regression coefficient; F = Fisher's F ratio; R^2 = Coefficient of determination (non-adjusted); SE = Standard Error.
* $p < .05$ ** $p < .01$ *** $p < .001$.

Similar to the findings for life satisfaction, the number of social uses was associated with health satisfaction. As in case of predicting life satisfaction, this association was more pronounced in the model with the short social uses scale than in the model with the full one.

With respect to other associations, men and residents of large urban localities were found to be less satisfied with their health than women and residents of rural localities, respectively. Respondents who reported being married and having high income were found to be more satisfied with their health than respondents who reported being unmarried and having mean or lower income, respectively.

Table 7 shows the results of the linear regression analyses predicting health satisfaction by each social use of mobile phone while controlling for the socio-demographic background.

Table 7. OLS analysis of health satisfaction by engagement in particular social uses of mobile phone – each one (Models 1-6) and altogether (Models 7-8) (n = 4839).

	Model 1 b (SE)	*Model 2* b (SE)	*Model 3* b (SE)	*Model 4* b (SE)	*Model 5* b (SE)	*Model 6* b (SE)	*Model 7* b (SE)	*Model 8* b (SE)
Constant	6.58***	6.37***	6.12***	6.07***	6.37***	6.32***	6.10***	5.94***
Phone calls	-.12 (.08)	---------	---------	---------	---------	---------	**-.15* (.08)**	---------
SMS	---------	.06 (.07)	---------	---------	---------	---------	-.02 (.07)	---------
E-mails	---------	---------	**.26*** (.06)**	---------	---------	---------	**.22** (.07)**	**.22** (.07)**
Instant messaging	---------	---------	---------	**.28*** (.06)**	---------	---------	**.22** (.07)**	**.22** (.07)**
SNS	---------	---------	---------	---------	.07 (.06)	---------	-.11 (.07)	-.11 (.07)
MMS	---------	---------	---------	---------	---------	**.18** (.07)**	.11 (.07)	.10 (.07)
Female (ref.)								
Male	-.21*** (.06)	-.21*** (.06)	-.21*** (.06)	-.20** (.06)	-.21** (.06)	-.21** (.06)	-.20** (.06)	-.21** (.06)
Age	.002 (.01)	.003 (.01)	.01 (.01)	.01 (.01)	.003 (.01)	.004 (.01)	.01 (.01)	.01 (.01)
Non-tertiary education (ref.)								
Tertiary education	.13* (.06)	.12 (.06)	.11 (.06)	.11 (.06)	.12* (.06)	.12 (.06)	.10 (.06)	.10 (.06)
Mean or lower income (ref.)								
High income	.46*** (.06)	.45*** (.06)	.43*** (.06)	.44*** (.06)	.45*** (.06)	.45*** (.06)	.42*** (.06)	.42*** (.06)
Non-married (ref.)								
Married	.33*** (.06)	.33*** (.06)	.32*** (.06)	.32*** (.06)	.33*** (.06)	.33*** (.06)	.31*** (.06)	.31*** (.06)
Rural (ref.)								
Small urban	-.12 (.07)	-.12 (.07)	-.13 (.07)	-.13 (.07)	-.12 (.07)	-.13 (.07)	-.13 (.07)	-.13 (.07)
Large urban	-.17* (.08)	-.17* (.08)	-.18* (.08)	-.18* (.08)	-.17* (.08)	-.18* (.08)	-.19* (.08)	-.19* (.08)
Israel (ref.)								
Austria	.40** (.13)	.40** (.13)	.43** (.13)	.45** (.13)	.43** (.13)	.42** (.13)	.43** (.13)	.43** (.13)
Canada	.04 (.13)	.08 (.13)	.13 (.13)	.21 (.13)	.08 (.13)	.09 (.13)	.19 (.13)	.22 (.13)
Finland	.26* (.13)	.27* (.13)	.30* (.13)	.32* (.13)	.29* (.13)	.25 (.13)	.28* (.13)	.29* (.13)
Netherlands	.25 (.15)	.28 (.16)	.28 (.15)	.28 (.15)	.27 (.15)	.31* (.15)	.29 (.16)	.30 (.15)
Romania	.17 (.15)	.23 (.15)	.33* (.15)	.33* (.15)	.23 (.15)	.26 (.15)	.36* (.15)	.40** (.15)
Spain	.23 (.13)	.27* (.13)	.25 (.13)	.22 (.13)	.25 (.13)	.29* (.13)	.21 (.14)	.24 (.13)
F	8.64***	8.52***	9.92***	9.92***	8.55***	9.01***	8.31***	9.04***
R^2	.024	.024	.028	.028	.024	.025	.032	.031

Note. MMS = Multimedia Message Services, OLS = Ordinary Least Squares, SMS = Short Message Services, SNS = Social Networking Sites.; b = Unstandardized regression coefficient; F = Fisher's F ratio; R^2 = Coefficient of determination (non-adjusted); SE = Standard Error

* $p < .05$ ** $p < .01$ *** $p < .001$.

In contrast to life satisfaction, only three uses—namely e-mailing, using MMS, and instant messaging—were found to be positively associated with health satisfaction. Yet when the use variables were included in one model (Model 7 and Model 8), only e-mailing and instant messaging were associated with greater health satisfaction. In contrast, voice calling appeared to exhibit a negative, though marginally significant, association with health satisfaction (Model 7).

DISCUSSION

This study investigated the associations between socio-demographic background and social uses of mobile phone, as well as between these uses and two subjective wellbeing measures—life satisfaction and health satisfaction—among retired Internet users. As to the former associations, the results supported and complemented earlier findings reporting digital divides in the adoption and use of ICT in general (Chopik et al., 2017) and mobile communication technology in particular (Cheng et al., 2015; Petersen et al., 2016). As to the latter associations, the results revealed not only the relationship between overall social uses and subjective wellbeing, but also the associations that are specific to certain social uses, generally supporting the uses and gratifications approach.

Regarding the RQ1 and the RQ2, the analysis confirmed that social uses of mobile phone are affected by digital divides. As a response to RQ1, being male, of younger age, having a tertiary education and a high income, being married and residing in large urban localities were associated with greater numbers of social uses performed (Table 2). As to RQ2, age was related to all studied social uses, whereas education, income, gender, marital status, and residential locality appeared to be the less consistently associated variables (Table 3). The results considering the age are consistent with other studies on ICT use (Berner et al., 2015; Chang et al, 2015; Chopik et al., 2017). Health tends to deteriorate with age (Mesch, 2016). In addition, offline social networks of older adults tend to dwindle for various reasons, including retirement (Cotten et al., 2013). All this may hamper the use of ICT use in general and in social uses of mobile phone in particular, as the elder people may have less ability, need, interest and/or motivation for engaging in these uses. The results on education are also in line with previous findings (Chang et al., 2015; Chopik et al., 2017; Friemel, 2016). Education reflects greater interest in ICT use (Berner et al., 2015), and lower perceived barriers in ICT use (Chopik et al., 2017) that, in turn, enable a broader scope of mobile phone uses, including those performed for sociability purposes. In addition, similar to other studies on ICT use (Friemel, 2016; Hargittai & Dobransky, 2017), income level was found positively associating with social uses of mobile phone. Higher income reflects better financial abilities (König et al., 2018), which allow purchasing more advanced mobile phones with up-to-date social functionalities. Regarding gender, older women were more likely to use instant messaging and particularly SNS than older men (also, e.g., Ihm & Hsieh, 2015). This result is in line with the gender socialization perspective, according to which women value and engage in communication, cooperation and social bonding to a greater extent than men (Merchant, 2012; Yu et al., 2016). Finally, residing in large localities may provide more reasons for increased social usage of mobile phone than residing in rural localities. Compared to their rural counterparts, older Internet users residing in large cities may have better digital skills which allow greater variety and sophistication of social uses of mobile phone.

As for RQ3, in line with earlier studies (Nimrod, 2020a) and with U&G theory (Han et al., 2015; Heravi et al., 2018), it was found that the number of social uses were positively associated with life (Table 4) and health (Table 6) satisfaction. These results imply that older adults use mobile phone also to gratify their sociability needs. Greater gratification of sociability needs via the mobile phone seems to result in greater subjective wellbeing.

Regarding RQ4, the results of the study show that instant messaging, using SMS, and e-mailing were positively associated with life satisfaction – both as separate predictors and when incorporated in the same model with the other uses (Table 5). In addition, only three social uses of mobile phone were found to be associated with health satisfaction (Table 7): e-mailing (positively), instant messaging (positively), and voice calling (negatively). These findings can be also interpreted through the U&G theory. The gratification of sociability needs using text-based mobile communication channels (e-mailing, using SMS and instant messaging) calls for good health in terms of dexterity and vision. In addition, they enable not only one-to-one but also one-to-many communication, thus allowing gratification from multiple social encounters at one point of time. Voice calls, in turn, are typically performed in a one-to-one mode, and are perhaps considered a more gratifying and suitable medium of communication when one's health status is poorer. All in all, the finding suggest that some social uses of mobile phone are more relevant than others for increasing the wellbeing of older adults, therefore justifying the use of the toolkit approach (Smock et al., 2011). More research is necessary to address these issues.

LIMITATIONS AND FUTURE RESEARCH

This study has some limitations that must be considered when interpreting the results and designing the future studies. First, the study is based on a cross-sectional design. Therefore, it cannot be concluded that the study participants report greater subjective wellbeing *because* of the larger number of their mobile phone uses or because of the engagement in particular mobile phone uses. As we have previously discussed, greater wellbeing may also expand the scope of social uses of mobile phone. Second, even though the samples from each country were representative of older Internet users by gender and age, the respondents included in the sample are likely to be in good health and to have good digital skills compared to other people in their age. This may be the reason why many of them engaged in social uses of mobile phone and why they were able to participate in the online survey which was relatively long and required retrieving of detailed information about ICT and media behavior (for example, number of hours and minutes of watching television via a TV set) instead of mere reporting about attitudes toward ICT. Third, the sample was skewed towards male, less educated, younger age and lower income users – characteristics that may restrict the generalization towards all older Internet users as well as influence the results of the study. Fourth, the measures of individual mobile uses are only indicative of whether or not respondents use mobile devices in general, which narrowed down the number of applicable statistical methods. Hence, future studies should also examine the frequency of mobile phone uses for social purposes and its bearings on wellbeing. Moreover, our data did not contain information about the reasons, goals and motivations behind the each of social uses of mobile phone. Instant messaging via mobile phone can be used for totally similar or completely dissimilar reasons as voice calling. In addition, use of SNS via mobile phone can gratify one need for one group of older Internet users but multiple needs for another group of them. Future studies should also address the role of the underlying factors, as they may correspond to the wellbeing outcomes in different ways. Fifth, because the wellbeing variables are based on self-reports, they may be subject to incorrect estimation due to social desirability. Finally, although significant associations were found between the studied variables, the explained variance was modest, especially in models predicting the subjective wellbeing. Other variables such as attitudes may provide a better explanation of the outcomes (Nikoloudakis et al., 2018).

CONCLUSION

To conclude, two main issues arise from the findings. First, a wide range of socio-demographic factors still differentiate between older adults who use and who do not use social functionalities of mobile phone. Consequently, this implied that the second level digital divide is still a considerable issue even in the sample consisting of people who were all Internet users and therefore probably more technology savvy on average than their agemates who do not use the Internet. Therefore, public decision makers and broader community should still stay alerted and be more involved in mitigating this divide, with special emphasis placed on elder people, those with lower levels of education and lower income. Second, social uses of mobile phone were positively associated with subjective wellbeing measures.

This implies that the use of mobile phones for social purposes seems to aid older adults to gratify their daily needs. The results also imply that e-mailing and instant messaging seem to gratify these needs to a greater extent than other uses. This said, the potential of mobile phones to alleviate the social isolation and loneliness, which tend to increase with age (especially with the transition from work to retirement) and have become accentuated with shelter-in-place policy as well as now with the COVID-19 pandemic, is evident. Therefore, older adults, especially those retired, should be further encouraged to use their mobile phone for social purposes. What needs to be carefully followed in the future is various life course trajectories shape the use of mobile communication for social purpose and its impact on personal wellbeing.

Statement of ethical approval

Principal investigators in Canada, Israel, Romania and Spain obtained ethics approval from their Institutional Review Boards (IRBs). In Austria and the Netherlands, there were no IRBs at the institutions involved. In the Netherlands, the head of department gave his ethic approval. In Finland, ethical review was not required according to the standards of the Finnish National Board on Research Integrity.

Statement of conflict of interest

The authors declare that there is no conflict of interest.

Declaration of contribution of authors

DR performed the statistical analyses and wrote all chapters of the manuscript except for Discussion. ST planned the study, coordinated the data collection, wrote the Discussion chapter, revised the manuscript and made necessary corrections.

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Consent to participate

Informed consent was not obtained from study participants since they were surveyed anonymously.

Data availability statement

The database of this project is not yet available to the public.

Short bio

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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.

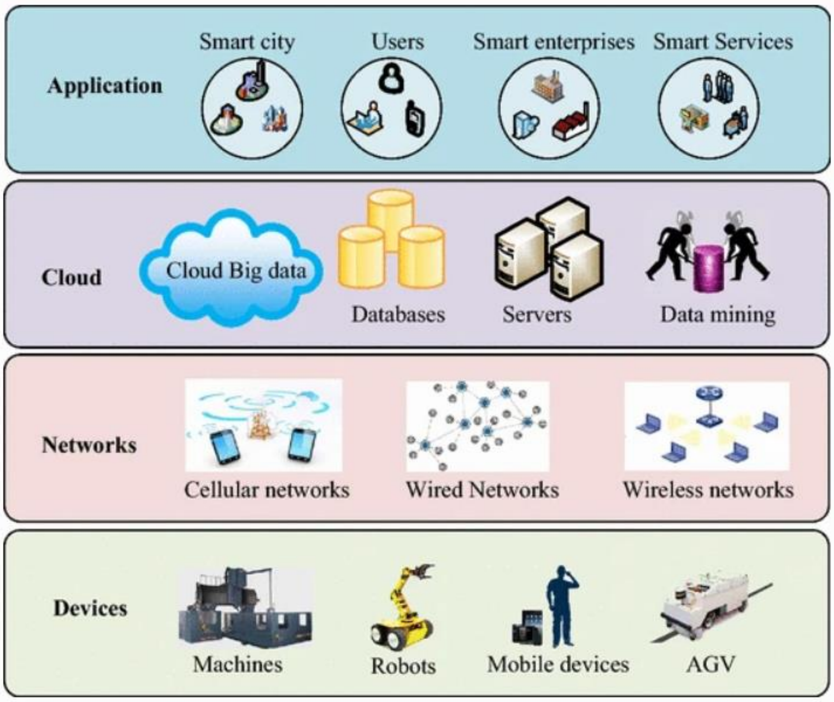


Figure 1. Basic Industry 4.0 Architecture (LI XM, 2017)

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).

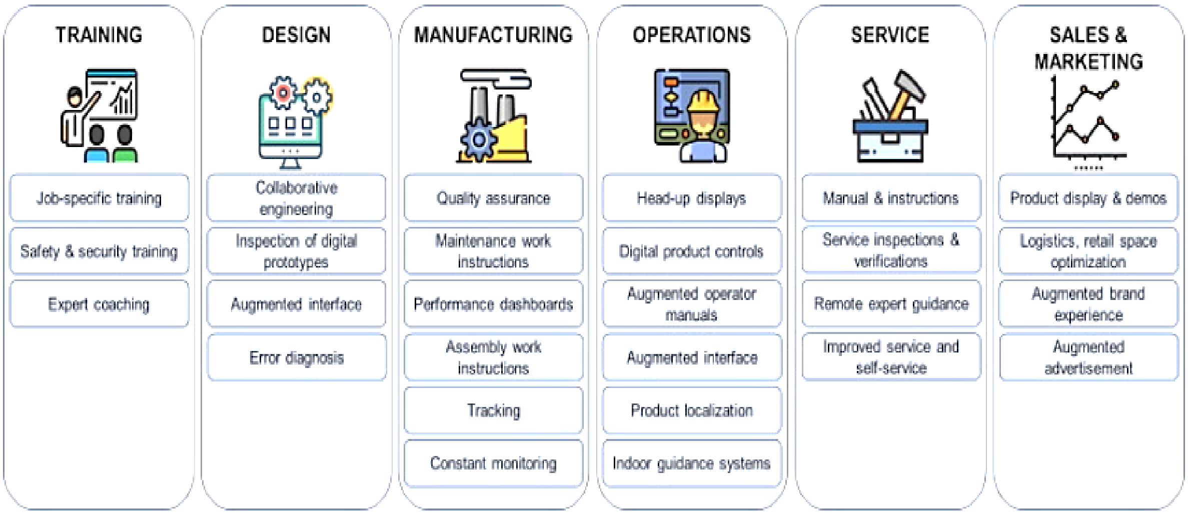


Figure 2. Six core areas for AR implementation (Alcacer, 2019).

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.

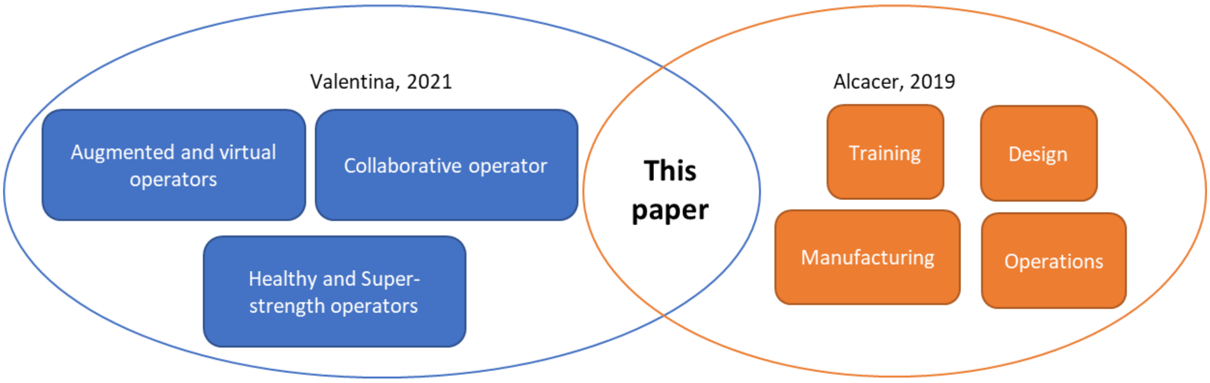


Figure 3. Concept of this article (own design).

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.

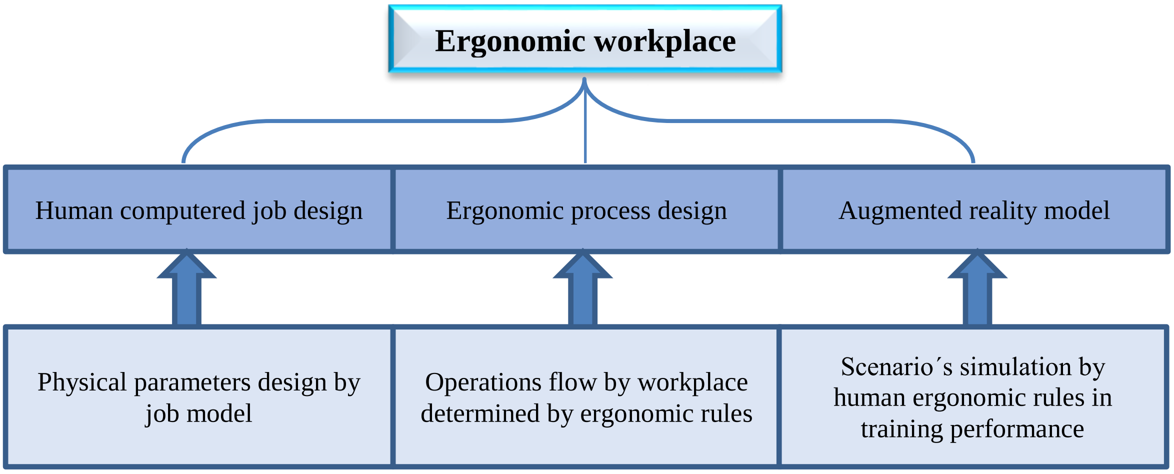


Figure 4. Combination of ergonomics and AR in 3 main pillars (own processing).

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.

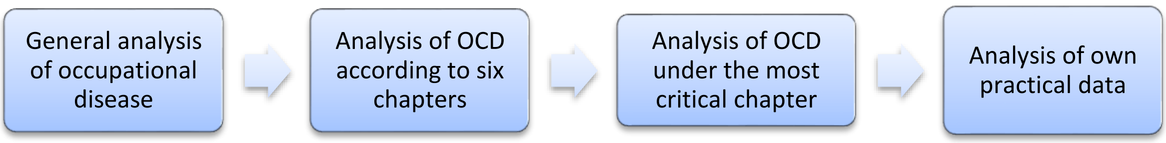
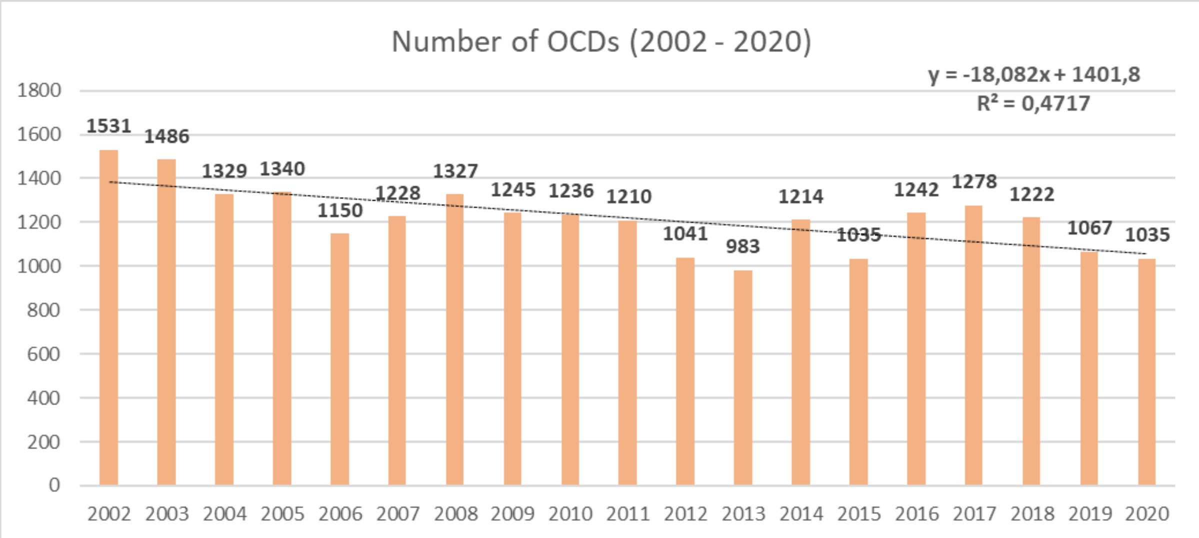


Figure 5. Individual steps of the case study (own design).

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).

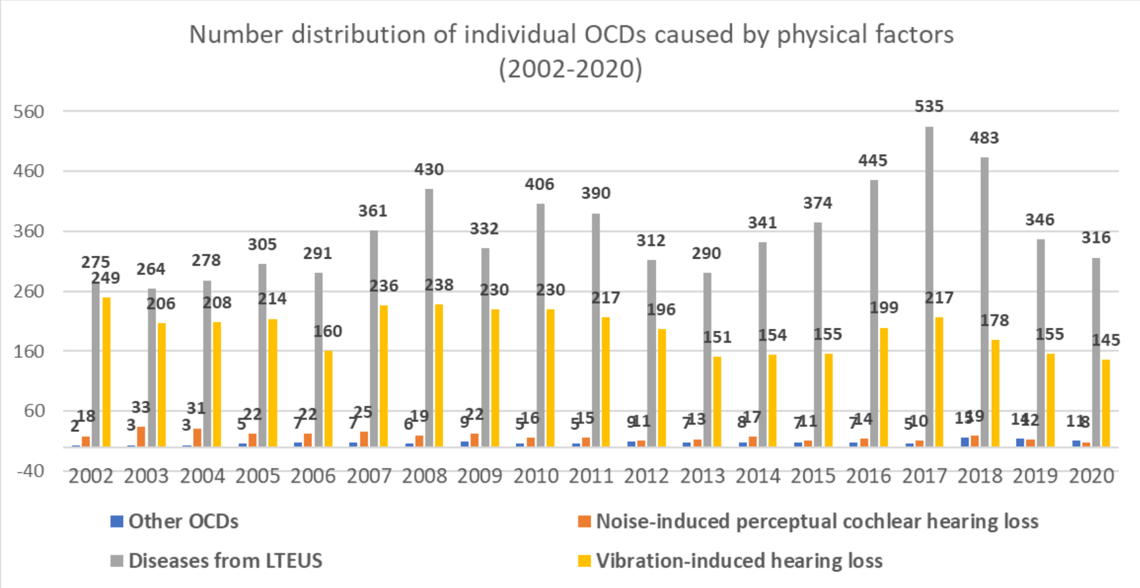
Popis	abosult frequency	relative frequency	ni2		
Man	806	32%	649636	Mutability=	**0,44**
Woman	1716	68%	2944656		
Total	2522	100%	3594292		

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

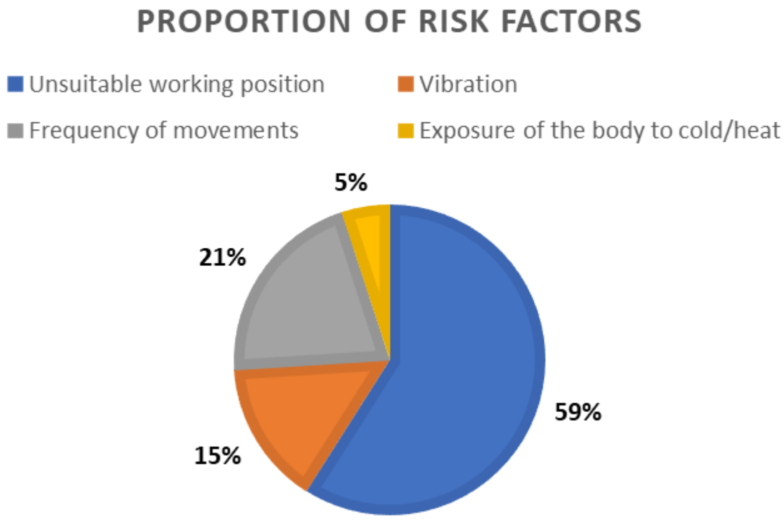


Figure 6. Proportion of risk factors in % (own design).

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	(ā - a)2	(b̄ - b)2	(c̄ - 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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