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Organizational culture of military institutions with regard to the gender aspects: A systematic review

Eva Štěpánková[1], Kristýna Binková[1], Petr Čech[1], Anna Karadencheva[2]

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Abstract

The values, norms, attitudes, and symbols within military organizations have traditionally been somewhat aligned with masculine traits. The aim of this paper is to investigate the precise manifestations of masculinity within the organizational culture of military institutions and to compare it with formal efforts and politics. The systematic review identified existing peer-reviewed literature in English or Czech in two electronic databases - Web of Science and Scopus. It was performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The results confirm the expectation that, despite formal instruments and standards supporting gender equality, the military is an organization still strongly based on masculine characteristics and associated with values and norms traditionally attributed to men. Nevertheless, in line with broader societal movements toward gender equality, there is some evidence of an attempt to integrate feminine aspects into the organizational culture of military institutions.

Keywords: organizational culture, military, gender, gender equality, systematic review

Introduction

The organizational culture can be defined as a set of shared ideas that organizational members adopt in an effort to adapt to the environment and to foster internal cohesion. It is imparted to new employees as the correct understanding of organizational facts, the correct way of thinking about these facts, and the desired emotional relationships toward these facts (Schein, 1985). Organizational culture, therefore, possesses a normative character. New employees must quickly orient themselves in the given environment to follow the required values and norms and understand what behavior is tolerated or, conversely, penalized. Organizational culture encompasses the symbols, values and norms and basic assumptions (Schein, 1992).

The symbols are easily observable and can be divided into material (e.g. logo, architecture, dress code, workplace design and equipment) and immaterial (e.g. customs, ceremonies, language, heroes). Values and norms regulate how members of an organization should behave. The basic assumptions are quite stable and resistant to change. They are based on the previous experience of how to solve problems (Lukasova et al., 2004).

Historically, the military has been characterized as a patriarchal institution, rooted in masculine values, norms, and stereotypes (Golan, 1997). Throughout history, military, defense, and security-related organizations have predominantly been male-dominated, with masculinity exerting a significant influence on their organizational culture and practices (Kronsell, 2005). Military culture is often described as competitive, disciplined, and hierarchical (Higate, 2003), as cited by McCallister, Callaghan & Fellin (2018). This culture has traditionally placed a premium on 'manly' characteristics, including heterosexuality, competitiveness, dominance, rationality, and physical strength. Research on the role of women in the armed forces has been plagued by numerous stereotypes, such as portraying men as 'just warriors' and women as 'beautiful souls' (Elshtain, 1995), or as Tickner put it, 'to be a soldier is to be a man, not a woman' (Rokvić, Stanarević, 2016). Even today, the presence of women in the military is often considered 'atypical' and 'unusual' (Atzori et al., 2008). The prevailing military masculinity culture stands in stark contrast to a civilian 'feminine' one (Alvinius, Holmberg, 2023). Nevertheless, in recent decades, numerous formal instruments have been developed to promote gender equality.

The research question of the paper is stated as follows: Do the norms and values established by formal instruments and gender equality standards align with the organizational culture of military institutions in their daily expressions, encompassing non-formal attitudes, values, and assumptions?

Methods and Data

A systematic review was performed under the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) updated in 2020 (Page et al., 2021). PRISMA offers an established, peer-accepted methodology that incorporates a guideline checklist, diligently adhered to in this paper, to enhance the quality control of the revision process and ensure its replicability.

Eligibility Criteria

The selection criteria were established according to the research question, and the results were organized in a table. To address our specific research question, the inclusion criteria included (I) articles written in English or Czech, (II) papers published in peer-reviewed academic journals between 2010 and 2023, (III) original research studies and (IV) solely articles examining the organizational culture of military institutions with regard to the gender aspects. Non-English and non-Czech language articles, reviews or guidelines, letters to the editor, conference abstracts, and dissertation theses were excluded.

Search Strategy and Selection Process

A search strategy was performed on two electronic databases (Web of Science and Scopus) during September of 2023. Databases were searched separately by two researchers. To improve the chances of finding relevant sources, Boolean Operators were used to combine search terms and its derivatives: ("military" OR "armed forces" OR "army"...) AND ("gender equality" OR "gender integration" OR "feminine" OR "masculine"...) AND ("organizational culture" OR "corporate culture" OR "shared values"...).

The articles from both databases were imported into the Rayyan systematic review software (Ouzzani et al., 2016) to proceed with the selection process. A multi-stage process was performed by four of the researchers, as follows: inclusion of articles from both databases in the Rayyan software, exclusion of repeated articles and articles in non-English and non-Czech languages (identified by the software), screening of the titles and abstracts, elimination of articles with no full text available, analysis of full texts of potentially relevant articles, integration of results of included articles and their comprehensive examination.

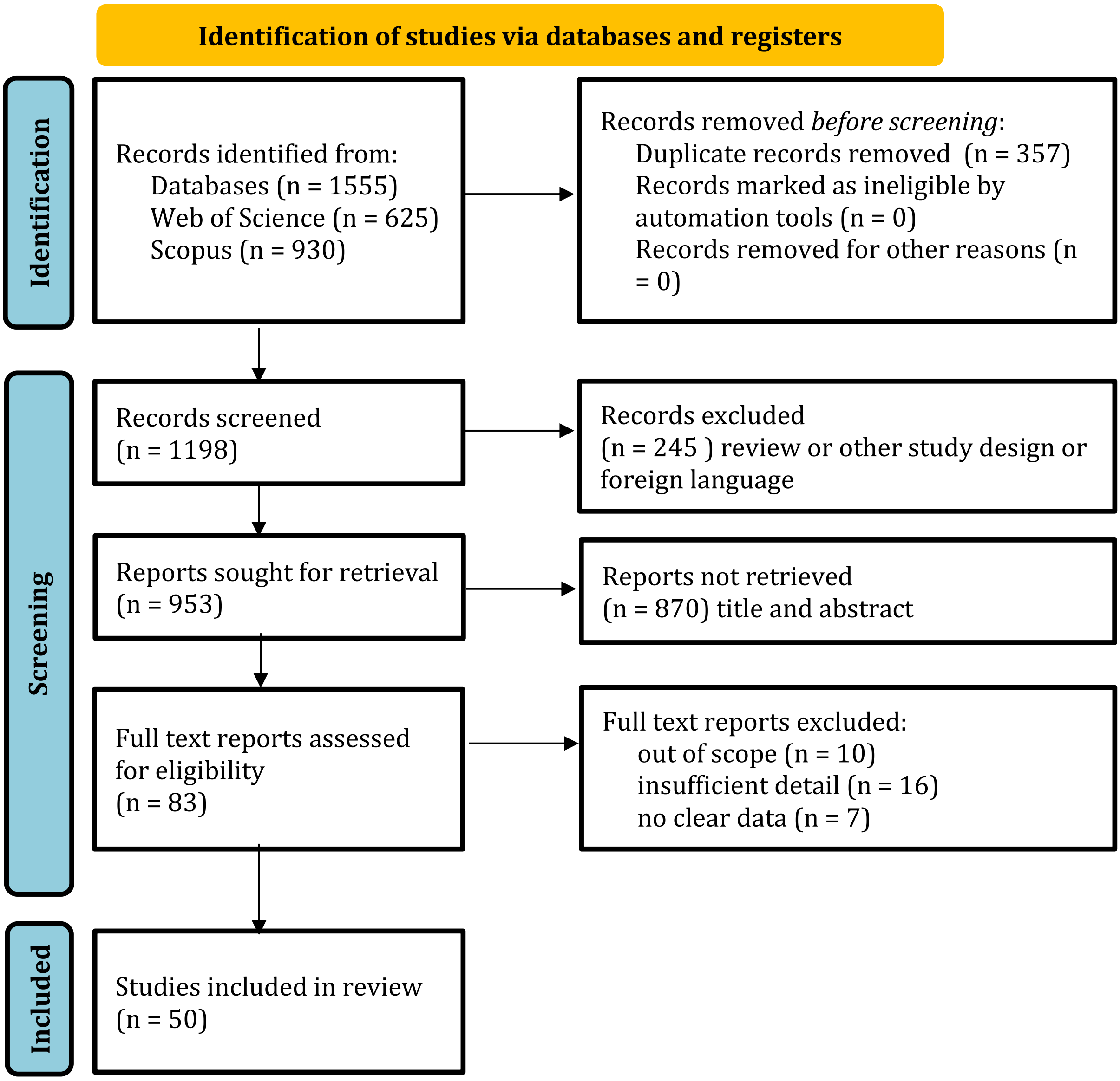
Data Extraction Process and Quality Assessment

All four researchers independently conducted data extraction and assessed the quality of articles. They recorded the data extracted from each study in an evidence table. Any differences were resolved through consensus when necessary.

Results

In the initial database search, we identified 1555 records. Following the removal of duplicate entries, we examined 1198 records. Of these, 245 studies were excluded due to their use of a review methodology, an alternative study design, or being in a foreign language (non-English and non-Czech). This left us with 953 records to screen based on their titles and abstracts, and 870 of these were eliminated as they didn't directly address our research question. In the final stage, we thoroughly reviewed the full text of the remaining 83 articles, excluding some due to insufficient information. Ultimately, 50 articles met our inclusion criteria for the review (as illustrated in Figure 1).

Graph 1: Flow chart diagram of the study process



Source: (Page et al., 2021), modified by authors

The findings are as follows: The number of women in the armed forces of major nations around the world is on the rise, albeit at a relatively slow pace. Barriers to women's entry into the military are gradually diminishing. Several organizations, including the UN and NATO, have emphasized in their official documents that the inclusion of women in all aspects of society is essential for achieving peace, economic prosperity, and social development (Rokvić, Stanarević, 2016). Examples of these efforts include the Beijing Declaration and Platform for Action, UN Security Council Resolution 1325, and Women, Peace, and Security Norms (Baek, Skjelsbaek, 2023; Rokvić, Stanarević, 2016). However, a lingering question remains: How do these formal tools impact the daily lives of men and women in the military, and are organizational culture, along with non-formal relationships, norms, and attitudes, changing in response to these initiatives?

The analyzed studies identify a variety of norms that manifest in the everyday life of military institutions, often linked to military objectives such as combat, survival, and fulfilling wartime missions. These norms encompass attributes such as physical toughness, courage, teamwork, competence, stress management, discipline, resilience in the face of pain or physical discomfort (Alfred, Hammer & Good, 2014), perceived stigma related to seeking mental health care, and externalizing behaviors, including risk-taking, violence, and substance abuse (Jakupcak, Primack & Solimeo, 2017, as well as references to Lorber and Garcia (2010) in Jakupcak, Primack & Solimeo, 2017, and McCallister, Callaghan & Fellin, 2018). Additionally, there is a desire for status and control, emotional regulation, tolerance for violence, a drive to win, and both hostile and benevolent sexism (Schaefer et al., 2021b).

The revealed aspects of the military organisation culture – values, assumptions and attitudes – are categorized into broader themes in the following text: (I) Sexism, (II) Unit cohesion and team spirit, (III) Unsuitability of women for the military, (IV) Physical and mental fitness, (V) Combat roles, (VI) Power and leadership, (VII) Restrictive emotionality.

Sexism

Several studies focus on sexism in the military. The specific manifestations may include impersonal sexual harassment, sexual preferences, hostile and benevolent sexism (Schaefer et al., 2021b), and the demonstrative presence of pornographic magazines and films (Pettersson, Persson & Berggren, 2008). Women are often expected to conform to the roles of 'sexual object,' 'hunting trophy,' or 'protected being' (Carreiras, 2006).

Sexism appears to have a significant relationship with men's attitudes toward women in the military. In a Croatian study by Trut, Hozo & Mladovcić (2023), sexism emerged as the most significant predictor of attitudes toward women in the military. According to Schaefer et al. (2021a), men with sexist beliefs tend to rate women lower in terms of military behavior and physical fitness. Additionally, there is evidence that men's appreciation of certain attributes of femininity is influenced to some extent by sexual behavior (Lakika, Palmary, 2022).

Some authors suggest that fostering a healthy balance between emotions and sexuality can help mitigate toxic expressions of masculinity in the military (Schaefer et al., 2021b).

Unit cohesion and team spirit

Military groups cultivate a caring, communal ethos built on strong interdependent bonds. A young soldier who can effectively handle the stresses of military life "embraces the soldier identity" and gains the benefits of protective factors, particularly the camaraderie that is inherent in military service. This paradox between hypermasculinity and nurturing masculinities within military culture is evident (Green et al., 2010).

Group dynamics within the military significantly influence unit cohesion and combat performance. Some authors argue that the inclusion of women in the armed forces may give rise to issues such as lower physical performance, fraternization, and sexual harassment, which could potentially have a negative impact on unit cohesion, morale, and the fighting spirit of the armed forces (Mitchell, 1998). Women are sometimes accused of distracting male fighters (Alvinius, Holmberg, 2023), and the presence of LGBTQ individuals may also pose challenges to cohesion and lead to conflicts within units (Rokvić, Stanarević, 2016).

Men tend to more readily participate in coalitions oriented toward the use of violence, especially in competitive environments. Such male coalitions often demand less initial investment and may exhibit greater durability than female coalitions when confronted with in-group conflict. The introduction of women into these coalitions can sometimes reduce cohesion, as men may find it challenging to trust women (Browne, 2012).

The concern that the integration of women into the military impairs readiness due to a decrease in unit cohesion is also supported by Collins-Dogru, Ulrich (2017). Male bonding and camaraderie often exist precisely because women are excluded. The bond of masculinity is a crucial value within military groups – a bond that women may not easily partake in (Marlowe, 1983).

Unsuitability of women for the military

The military often perpetuates a cult of the warrior hero (Mokua, 2015b). Traditional military attributes, such as strength and physical courage, have historically been crucial for warriors. However, women may face challenges in gaining the trust of their male comrades in the same way that men can (Browne, 2012).

According to common military opinion, there are perceived differences between men and women in various psychological dimensions relevant to military performance. Men are often viewed as more independent, confident, driven, and better leaders, while women are often seen as kinder, gentler, and better at expressing their emotions than men (Boldry, Wood, 2001). States that femininity is often regarded as 'inconsistent' with military service (Herbert, 1998), and some mention a perceived unsuitability of women for 'masculine roles' (Mokua, 2015a).

According to Persson, Sundevall (2019), men are often considered the standard against which women in the military are measured. Women serving in the military frequently face scrutiny and criticism, as noted by Herbert (1998). In practice, men tend to express more negative attitudes toward women in the military when compared to other men, as observed in the study by Trut, Hozo & Mladovcić (2023). Holder (1996), as cited by Atzori et al. (2008), illustrates that women often struggle to gain acceptance in traditionally male work groups, regardless of their performance, mentality, or level of preparation. An American study by McSally (2023) highlights that women in the defense sector may be treated as second-class troops without receiving the same benefits as men.

According to a survey conducted in Congo, it was found that when women actively engaged in combat, they needed to excel at their duties and sometimes even exhibit greater ruthlessness than men to earn the same privileged status as men (Lakika, Palmary, 2022). U.S. women combat veterans have reported a persistent need to conform to masculinity norms and exhibit behavior considered appropriate for men in order to fit in with their peers (Richard, Molloy, 2020). Women soldiers who embrace masculinity norms tend to report more successful performance in combat roles (King, 2016).

Women in the military are often expected to conform to male norms. Unassertive behavior by a woman may lead others to perceive her as less talented and undermine her authority (Karazi-Presler, Sasson-Levy & Lomsky-Feder, 2018).

Physical and mental fitness

Many masculine values, including physical toughness, courage, teamwork, competitiveness, stress management, discipline, and the ability to endure pain and physical discomfort, are essential traits for the demanding tasks of combat, survival, and mission accomplishment (Alfred, Hammer & Good, 2014). These attributes are closely linked to the physical and mental fitness of soldiers.

Women are often regarded as physically weaker and having "insufficient" capacity to fulfil military duties compared to men. In terms of physical condition, as indicated by Epstein et al. (2013), both aerobic and anaerobic fitness levels are typically lower in women when compared to men. This lower overall work capacity means that women often need to exert themselves more than men to achieve the same level of output. Consequently, women may tire earlier and face an increased risk of overuse injuries. Additionally, the body structure of women predisposes them to a higher incidence of stress fractures, as observed by Epstein et al. (2013).

Several authors, including Mitchell (1998, as cited by Rokvić, Stanarević, 2016), and Persson, Sundevall (2019), have highlighted the perception of lesser physical ability. According to a respondent in a Danish qualitative study, "As a woman, you must prove that you are always good enough, especially physically, that you can keep up with the boys. You are not measured on your intelligence, but on how many pull ups you can take or how fast you can run" (Svop, 2021).

In this Danish qualitative study, marines often perceive women as unsuited for their service due to concerns about their physical strength, which is considered essential for the occupation. However, they also acknowledge that these differences could potentially be overcome through military training (Van Douwen, Van den Brink & Benschop, 2022). In contrast, another study argues that gender differences persist even after basic training (Epstein et al., 2013; McSally, 2023) and contends that the arguments suggesting women are not capable of combat or handling the stresses of military service have been disproved.

The physical and mental attributes of men are often constructed in alignment with traditional notions of violence and warfare, while women are commonly associated with concepts of peace and the giving of life (Tidy, 2018).

Several studies suggest that women often exhibit lower physical fitness levels than men. However, the issue arises when this physical difference is unfairly associated with aspects that are fundamentally unrelated to physical strength, such as sexism and leadership.

Combat roles

The inclusion of women in combat operations and roles is a topic of high debate. Despite formal policy provisions stipulating that women have an open career path in the military, there remains widespread resistance to women serving in combat roles (Mokua, 2015a). Nicolas argues that during her service in the US armed forces, she encountered two prevalent myths and stereotypes: "'women do not have upper body strength" and "women are too emotional to lead in combat" (Nicolas, 2014).

In a Portuguese survey, 60% of military cadets advocate for women's participation in all military tasks, including combat roles, while 20% believe that women should be limited to administrative, logistical, and technical support functions. Another 20% propose that women could undertake operational tasks but not engage in combat roles (Malheiro, Bessa & Reis, 2023). The traditional view of women in the war system is often as "mothers, wives, and sweethearts", "nurses, prostitutes, and social workers", rather than soldiers (West, Antrobus, 2023).

According to an Israeli study, female soldiers in both combat and non-combat units exhibited higher stress levels than their male counterparts. Female soldiers in combat roles were more similar to male soldiers than to female non-combat soldiers across several psychological measures, but they also reported feeling "more commitment and challenge" (Tarrasch et al., 2011).

Power and leadership

All the other groups mentioned above can be related to power and leadership in some way. Schaefer et al. (2021b) mention men's Machiavellian desire for status, control, and the need to win. Power, especially violent power, is often perceived as masculine (Connell, 1987), while women are frequently portrayed as lacking power and being victims of violence.

According to Karazi et al. (2018), power can be a source of both pleasure and empowerment, as well as shame for women in commander positions. Their exercise of power can lead to negative, critical reactions and ridicule. It challenges accepted gender norms by crossing boundaries and using military power traditionally reserved for men. The sense of shame may serve as a barrier that hinders women from pursuing positions of power in the future. Additionally, there are various other barriers to leadership, including personal, departmental, institutional, and societal obstacles (Zdravkovic et al., 2020).

Restrictive emotionality

Beliefs about women being more emotional than men are often used to justify gendered power imbalances. The requirement for emotional self-control, a masculine imperative, bestows prestige on men and positions them as superior to women (Sasson-Levy, 2008). This societal view may lead to the suppression of emotions.

As a consequence, soldiers may struggle to find a way to communicate their distress and problems (Green et al., 2010; Lorber, Garcia, 2010). Military training frequently emphasizes the importance of emotional control, as it's perceived to enhance survival and mission success (Lorber, Garcia, 2010). This form of "secondary socialization" (Arkin, Dobrofsky, 1978) is prominent in the Armed Services, where strict adherence to hypermasculine ideals is institutionalized.

Discussion

While the number of gender and diversity interventions has significantly increased, research indicates that they are often ineffective or even counterproductive. This is primarily due to resistance from organizational members driven by myths and persistent ideas (Lombardo, Meragert, 2013). Normative conceptions tend to reinforce dominant cultural patterns and actively contribute to their perpetuation (Carreiras, 2010).

Non-formal forces of segregation within the military persist (Collins-Dogru, Ulrich, 2017). Women represent a growing but still a minority in most Western militaries. In their daily activities, women often confront institutional norms deeply rooted in rituals, routines, symbols, and language that are defined without, or even against, them (Kronsell, 2005), leading to issues like discrimination, harassment, and sexual assaults (Davisa, 2022).

The impact of policies, standards, and norms for gender equality depends, among other things, on the region where they are implemented and the local mentality. For instance, in Norway, gender equality is considered a “natural” part of the national identity, and gender instruments are perceived as less relevant (Baek, Skjelsbaek, 2023). In countries with strong male-dominated cultures, such as Colombia, such policies are considered more relevant (Fernandez-Osorio et al., 2023), but they may be harder to enforce.

In military organizations, there are still numerous gender-related issues that disproportionately affect women. However, there have been some positive findings about the impact of the military environment on women. For example, Shahrabani, Garyn-Tal (2019) confirmed the positive impact of military service on women's self-efficacy and risk attitude.

Based on the study of sources, the following suggestions can be formulated to improve the situation in the field of gender aspects of military organizational culture:

- Integration of Women in Ground Combat Roles: This includes special forces' operators. The aim is to reduce discrimination and gain respect in a male-dominant culture (Reis, Menezes, 2020).
- Mixed Living Arrangements: The positive effects of males and females living together in mixed rooms are notable. This can promote mutual understanding, de-sexualization, and reduce sexual harassment (Ellingsen, Lilleaas & Kimmel, 2016). However, the impact may vary depending on the context. Integrating members of the opposite sex can help alter gender stereotypes (Dahl, Kotsadam & Dan-Olof, 2018).
- Role of Military Academies: Military academies play a significant role in fostering cohesion and respect for women's rights. They contribute to a more gender-neutral environment (Fernandez-Osorio et al., 2023).
- Business Case Argument: The argument that women contribute to the organization's goals may be more persuasive than moral arguments (Egnell, Hojem & Bert, 2014).

However, as a public institution, the military must also conform to gender equality for reasons unrelated to profitability arguments (Holmberg, Alvinius, 2023).

- Emphasis on Data and Technology: With the increasing emphasis on data, science, research, and technology, there is less dependency on physical force and presence on the battlefields. Women military personnel do not necessarily have to participate in direct combat. Those with the most appropriate knowledge and technical competence can still be part of this new system of warfare (Mokua, 2015a). Some 'close combat roles' may still be an exception. Importantly, there is no direct evidence that women have a negative impact on combat effectiveness (Epstein et al., 2013).
- Leadership and Training: Sexist attitudes can be overcome through proper leadership and training (Browne, 2012).

Moreover, an Israeli study on women soldiers revealed that they shape their gender identities according to masculinity norms through these practices:

- Mimicry of Combat Soldiers: This involves adopting both bodily and discursive practices while distancing themselves from "traditional femininity."
- Trivialization of Sexual Harassment: This practice is a complex one, signifying both resistance and compliance with the military's dichotomized gender order (Sasson-Levy, 2003).

Conclusion

Numerous formal instruments for gender equality have been established, both in society at large and within the military. These include international and national policies, norms, and standards aimed at promoting gender equality. However, several problematic areas within this topic need consideration.

First, while formal gender equality is fully affirmed in Western societies through these instruments, the day-to-day practices within military collectives often diverge from declared gender values and norms. The reality does not always align with the formal settings, and informal values and attitudes related to gender equality in the military persist. This conclusion is based on prior research findings.

Second, gender equality in the military, as in other spheres, can be interpreted in various ways. Some advocate for gender equality as equal participation of women in all military activities, including combat roles. Others view gender equality as the complementary involvement of male and female roles and characteristics, where both approaches are evaluated as equal, each offering unique benefits to the organization.

Interventions intended to promote gender equality may not yield the planned results, partly due to resistance. Rather than attempting to avoid resistance, it is crucial to better understand its underlying reasons (Van Douwen, Van den Brink, & Benschop, 2022).

Consistently monitoring dimensions aimed at aligning institutional decisions and internal communication is necessary (Malheiro, Bessa, & Reis, 2023). Political and societal gender pressures in the military often lead to various forms of resistance, making it challenging for women to assert their voices and introduce alternative feminine values. The effort should focus on integrating positive masculinities and positive femininities as valuable, even necessary, aspects of modern military organizations (Heinecken, 2017).

The subject is relevant due to the escalating social emancipation, denoting an increasing demand for equal access among individuals of diverse gender, race, or sexual orientation. The armed forces have also started working on these efforts, although presently employing primarily formal mechanisms. In order for representatives within this domain to effectively reshape everyday reality toward fostering equal opportunities, a preliminary step involves identifying the specific obstacles and understanding the experiences of women within such organizations. It is imaginable that individuals identifying as transgender or non-binary, along with those of non-heterosexual orientations, encounter analogous attitudes and stereotypes similar to their female counterparts. Exploring this hypothesis further through empirical means would undoubtedly prove beneficial.

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The circular solution to the functioning of breweries

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Abstract

The article aims to identify the key circular solutions used in breweries, the factors influencing the motivation for environmental responsibility and the implementation of circular measures. The research is carried out using the method of a quantitative questionnaire, which was sent to brewery owners. The obtained results contribute to a better understanding of circular solutions used in breweries, their motivation for environmental responsibility and the implementation of circular measures. The conclusions also show that the motivation of breweries for environmental responsibility is excellent, and most breweries implement many activities for environmental protection. Limitations of the research mainly include the limited number of respondents.

Keywords: environmental responsibility, circular economy, breweries, sustainability, waste, recycling

Introduction

Robert Ackerman and Raymond Bauer are considered pioneers of corporate social responsibility, or Corporate Social Responsibility (CSR) (Changling et al., 2022). The concept emerged in the 1970s. They assumed that more than real commitments from executive management alone would be needed and that the moral challenges associated with CSR initiatives should not overshadow the organisational and managerial dilemmas caused by CSR-based policies (Acquier et al., 2011). Horák and Pavlová (2022) states that the debate on corporate social responsibility and the strategies organisations implement to spread their entrepreneurial activities encourages discussion on aspects that point to sustainable development. One of the mechanisms companies uses is the presentation of sustainability reports to show their CSR strategies (Murillo-Avalos et al., 2021).

An economically responsible company does not have problems with customers with the workforce, pays its obligations on time, improves its negotiating position when dealing with investors or the government, and, thanks to this, strengthens its economic performance (Horák and Katz, 2022). The company acts transparently and plays fair play. Social responsibility includes caring for company employees, their working conditions and their environment (Tlustý and Kmecová, 2022). A satisfied employee is essential for the success of the company. An ethically responsible company most often uses a code of ethics. This document contains ethical behaviour principles and must be drawn up realistically and adhered to. A philanthropically responsible business deals with charity. Businesses support other persons or non-profit organisations (Chena and Jin, 2023)

Kliestik et al. (2020) state that environmental responsibility has recently been hotly debated. It represents responsibility towards nature and the environment. We are not indifferent to what happens to our planet; we must take care of it for a better life for us and future generations. After many years of devastating nature, it is also time to give something back to nature. It is essential to address this topic because every resource is exhaustible. The ecological crisis is pushing all companies into changes in management and the use of the circular economy (Dvořáková et al., 2021). Various national and international organisations are creating specific initiatives to improve the environmental crisis, currently the Green Deal. The document contained complete definitions of the concept and was adopted at the national, international and European levels (Horák and Dušek, 2022). The document is generally a strategy to mobilise communities and businesses to create a green economy by implementing environmental solutions in various sectors (Smol, 2022).

There are many breweries worldwide, and each has a huge water and electricity consumption. There is a need to solve this problem and somehow reduce or transform consumption, as breweries leave a large ecological footprint. This can be achieved with the help of the circular economy (Dvořák et al., 2018). According to Bellemare et al. (2022), the circular economy focuses on environmental sustainability, while the social economy primarily refers to economic democratisation, collective entrepreneurship and the search for the common good.

Hayhoe et al. (2019) state that the essence of the circular economy is to keep resources in use as long as possible, extract value from them during use, and restore and regenerate products and materials at the end of each lifetime. Circular water management optimises water resources and recovers valuable resources from water and wastewater while mitigating emissions and increasing resilience to climate change (Brears, 2020).

This article aims to identify how breweries in the Czech Republic approach environmental responsibility and whether they apply a circular economy in their operations. It also proposes, concerning demanding financing, procedures for applying or maintaining environmental responsibility.

To fulfil the stated objective, two research questions are defined. A null hypothesis (H0) and an alternative hypothesis (H1) are established for each research question.

VO1: What circular solutions do breweries in the Czech Republic use in the post-covid era?

H0: At least 80% of breweries in the Czech Republic use some of the circular solutions.

H1: Breweries in the Czech Republic do not use any circular solutions.

VO2: What is the motivation for environmental responsibility and the introduction of circular measures for breweries in the Czech Republic in the post-covid era?

H0: Breweries in the Czech Republic have a significant motivation for environmental responsibility and the introduction of circular measures.

H1: The motivation for environmental responsibility and the introduction of circular measures in breweries in the Czech Republic must be higher.

Literary research

The circular economy in connection with breweries is in the interest of several surveys, mainly because breweries are very demanding in their operation. Verhuelsdonk et al. (2021), for example, state that breweries have a huge water consumption and thus, reusing wastewater is appropriate. Rasmeni et al. (2022), in turn, state that a large amount of organic waste is produced during the production of beer, which pollutes the environment. The disposal of by-products from beer production represents large costs and public pressure on the sustainable operation of the brewery. Following this, specific research by Sehn et al. (2021) found that breweries use malt residues to feed animals in the countryside, the yeast biomass is dehydrated and converted into brewer's yeast that can be offered commercially as probiotics and hot water is reused to clean the environment and equipment. Terefe et al. (2023) investigated the use of thresher-feeding dairy cattle in Ethiopia on farms near breweries. Data collection was carried out using a semi-structured questionnaire. 80% of farmers reported that threshing spoils quickly, and the rest reported odour and mould. The problem is that the threshed reaches the farms very wet, and the farmers would have to dry it or put it in silage, increasing their costs. They conclude the research by saying that further investigation and research are needed to see if dairy cattle have any negative health issues. Dias et al. (2023) devoted their attention to brewery wastewater. According to them, wastewater could be purified with the help of oleaginous yeasts and algae microorganisms, which can reduce energy consumption and the formation of dangerous sludge and the costs of its treatment.

Morgan et al. (2022) assessed how the environmental impacts of packaging and distribution can be mitigated in microbreweries. They evaluated seven breweries and compared their existing packaging and distribution practices with three mitigation options; using aluminium cans or reusable glass bottles instead of disposable glass bottles or using polyethene terephthalate (PET) drums instead of steel drums. The findings show that all participating breweries can achieve reductions in multiple impact categories if single-use glass bottles are changed to aluminium cans or reusable glass; further reductions are possible if the mode of transport is changed from small vans to distribution truck retailers. Using a PET keg as an alternative to a reusable steel keg is a less environmentally sustainable option when shipping beer over short distances. Still, some savings are possible over long distances using vans. The optimal combination of truck-delivered reusable glass bottles reduces the carbon footprint by 45-55%, but implementation will require significant investment and coordination within the wider food and drink sector. Identifying the best packaging material requires a holistic approach considering the interactions and burdens across the manufacturing, distribution, use and end-of-life phases. For further research, they recommend focusing on cross-sectoral models to achieve optimised logistics and on the impact of new technologies such as packaging type and electric vehicle distribution to better understand the long-term prospects for mitigating the environmental impact of packaging and distribution.

Methods and Data

To fulfil the objective of this article and answer the set research questions, a quantitative research method will be chosen, namely data collection using a questionnaire. This questionnaire will be aimed at brewery owners. This is primary research, so it does not focus on any particular brewery size, rather it examines breweries in general as they exist in the market. Microbreweries do not share much information, so we decided to focus on larger breweries as well, namely Pilsner Urquell and Staropramen. Furthermore, a content analysis of the documents will be carried out. Specifically, the Annual Reports and Sustainability Reports of two large breweries in the Czech Republic – Pilsner Urquell and Staropramen – will be used. Within these documents, the strategic goals the breweries have set for their journey of environmental responsibility will be sought.

As outlined above, the questionnaire will be sent to brewery operators in the Czech Republic. Pilsner Urquell and Staropramen breweries also participated in this survey. The questionnaire will be created using the Forms tool from Google. It will consist of closed and open questions, which will be compulsory. A link to the questionnaire will be sent to breweries with a request to fill in and explain the purpose. This questionnaire will determine whether they consider themselves an environmentally responsible company, what circular solutions they use, their motivation for environmental responsibility and the introduction of circular measures. The research dealt with the content analysis of documents, where the paper has two areas that it deals with, one is the analysis of company documents in the context of the circular solution, the second part is the actual research in this area.

The data obtained from the questionnaire will be analysed using statistical methods using functions in MS Excel. Descriptive statistics will be used here to display the essential characteristics of the data, e.g.

average:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \tag{1}$$

median:

$$Me(X) = x_{(N+1)/2} \tag{2}$$

dispersion:

$$Var(X) = \frac{1}{N}((x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \cdots + (x_N - \bar{x})^2) \quad (3)$$

Based on the questionnaire, it will be possible to answer predetermined questions. As part of the first research question, various circular solutions used in breweries will be identified and categorised, such as the management of threshing, the use of waste for other applications, the use of environmentally friendly alternative sources and the effort to reduce the consumption of input resources. As part of the second research question, answers will be sought to inquiries about why breweries started circular economy, what circular solutions they use and whether they plan to start with a circular economy.

First, hypotheses H0 and H1 for VO1 will be tested. Categorisation of answers regarding circular solutions used in breweries will be done. The frequencies of individual solutions will be analysed and compared. If at least 80% of breweries use some circular solution, H1 will be rejected, and H0 will be accepted. To test hypotheses H0 and H1 for VO2, the responses regarding the motivation for environmental responsibility and the implementation of circular measures will be analysed. It will be evaluated whether the reasons given by the breweries for introducing circular measures indicate a significant motivation. If motivation is significant, H1 will be rejected, and H0 will be accepted.

After analysing each research question, the information obtained will be evaluated and the results interpreted. We will focus on identifying the key circular solutions used in breweries, the factors influencing the motivation for environmental responsibility and the implementation of circular measures.

Results

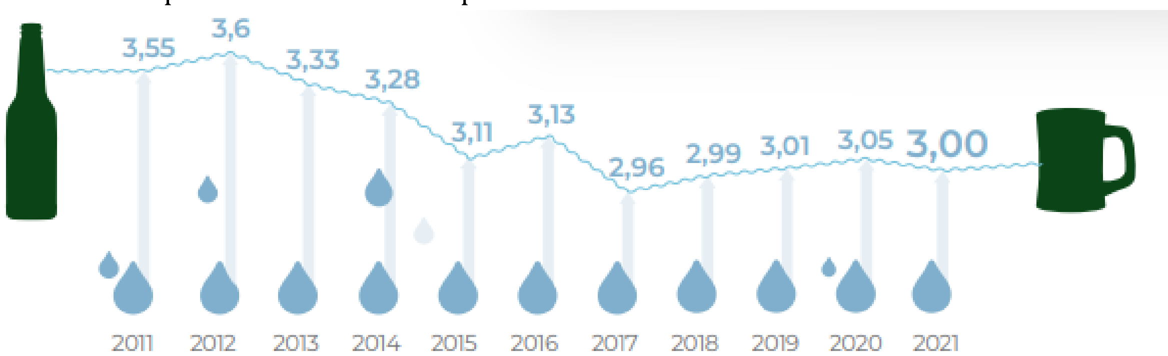
Based on the latest surveys, there were 515 breweries (480 microbreweries) in the Czech Republic in 2019, and in 2018 they produced 21,272 thousand hectolitres of beer, with microbreweries accounting for roughly 2.5% of this amount. A microbrewery can be considered a brewery whose beer production is at most 10,000 hectolitres. According to the Czech-Moravian Association of Microbreweries, microbreweries will increase slightly in the coming years.

We can distinguish 3 types of beer according to the fermentation method. They are bottom-fermented (the most widespread in the Czech Republic) lagers, topfermented ALE (highly hopped beer), and spontaneously fermented (Lambic). Then the Czech breweries produce, beers with reduced alcohol content and non-alcoholic. Furthermore, we can distinguish light, semi-dark and dark beers according to the colour. Light is brewed from light malts; semi-dark and dark beer are brewed from dark malt added in different proportions to the light malt.

Sustainability of breweries

Pilsner Urquell is the most engaged large brewery in environmental responsibility. Since 2006, it has published a Sustainability Report every year in addition to its Annual Report. In it, they state their goals for improving the environment and the current results in environmental engagement. In the 2021 report, Plzeňský Prazdroj (2022) set strategic goals for what it wants to achieve by 2025, 2030 and 2050. It intends to achieve carbon neutrality by 2025, thanks to the fact that all electricity for the breweries will be from renewable sources. Another goal concerns reducing the average water consumption needed to produce one hl of beer to 2.78 hl. Another plan focuses on waste. They want to ensure that none of their waste is in a landfill. Other strategic goals for the sustainability journey to 2025 relate to responsibility, in the sense that 90% of products will be produced with a reduction in sugar content or entirely without it, 20% of products will be non-alcoholic, and the last goal is to increase by 20% engagement in prevention programs. By 2030, they will reduce the carbon footprint of the supply-customer chain by 30%, water for their breweries will only be from sustainable sources, they will end the use of single-use plastics made from primary raw materials, all product packaging will be recyclable or reusable and at least half made from recycled materials, agricultural raw materials will be from sustainable sources, 25% of the products will be soft drinks, and the last goal is about diversity, they want to achieve a balanced proportion of men and women in management. By 2050, they want to achieve carbon neutrality across the entire supply-customer chain. They want to achieve carbon neutrality thanks to innovations and the modernisation of warehouses and malthouses (mainly replacing machines, boilers, and compressors). They use the heat supply as green energy by burning waste wood chips, which return almost 300,000 tons of burnt brown coal. Compared to 2020, total emissions were reduced by 0.67 MJ/hl, and in 2021 greenhouse gas emissions were reduced to 5.51 kg CO2 e/hl. Another contribution to carbon neutrality is using electric cars, which are currently being tested to see if the car's parameters cover the brewery's needs. They want to reduce average water consumption by investing in technology. They are now at 3L of water per 1L of beer, and downsizing is more complicated and slower. Figure No. 1 presents the development of water consumption per 1 litre of beer over ten years.

Figure 1: Development of water consumption



Source: Sustainability Report 2021 Plzeňský prazdroj.

They achieve sustainable agriculture thanks to using local raw materials suppliers, reducing their carbon footprint. They have reduced the consumption of single-use plastic from primary material by 80% since 2019. They use recycled paper for their bottled beer labels, saving 350 tonnes of new paper annually. Thanks to the innovation, the cans are 75% recycled aluminium, reducing the carbon footprint by 30% and saving 280 tons of new aluminium annually. They use glass bottles an average of 22 times. They leave the used stretch films to another company, which continues to process them, and the paper labels from the bottles. They leave the waste threshing as fodder for cattle and then make crackers for people from it; in 2021, they utilised 794 kg of threshing. Due to the pandemic, the produced beer could not be sold in pubs, so they let it be fired in cooperation with the L'OR company, which created PROUD SPIRIT beer brandy. They achieve equalisation of the representation of women and men in management by offering women on parental or maternity leave reduced working hours, flexible working hours, or a contribution to preschool facilities for children under three. They strengthen responsibility through education, e.g. prevention of underage drinking, destruction of prejudices regarding non-alcoholic beer, and reliable communication of products.

Another brewery on the market that publishes reports on sustainable development is Brewery Staropramen. It has been publishing them since 2017. Staropramen (2022) established two areas of interest PEOPLE (Employees and community, Responsible consumption and corporate governance) and PLANET (Sustainable production). Taking care of its employees is essential for Staropramen. He realises that properly motivated employees are the best team players and a great business card for the entire company. They promote diversity and equal opportunities. They have five men and three women in top management. Within the community, they are involved in various programs, volunteering and sponsorship. As part of Responsible Consumption, the company promotes responsible consumption within projects and communications, producing products with a low alcohol content or non-alcoholic. Various quality audits take place at the brewery several times a year, such as the Kosher audit, which concerns the product line for the Israeli market so that customers can be sure that the product meets the requirements of Jewish dietary habits and laws. They rely on correct and truthful labelling of products on all labels and packaging. The second area of PLANET deals with sustainable production. The brewery buys 80% of its raw materials and services from local suppliers; all suppliers are vetted to have a responsible approach to the environment and reduce their ecological footprint together. The brewery used the pandemic period to innovate and modernise its IT infrastructure. He set goals for 2025 to protect the environment by reducing water consumption per 1 hl of beer to 3.42 hl; in 2021, consumption was 4.05 hl. Other purposes include reducing the consumption of electrical and thermal energy and reducing waste that goes to landfills, specifically so that no litter ends in landfills. The energy used is steam from natural gas, such as air and cold from cooling compressors. They still monitor all consumption and efficiency. They reuse the water used for cooling and thus also use the removed heat. From 2020, the brewery bottled Braník and Staropramen beer with a 30% share of recycled plastic. It can contain 70-90% recycled material. Almost 95% of the waste is recycled, and the rest is used in an incinerator to produce energy. He sold nearly 48,000 tons of threshing and 36,000 hectolitres of yeast to feed manufacturers. Logistics reduces emissions by using large-capacity forklifts and electric or gas-powered trucks. It is gradually renewing its vehicle fleet to vehicles with the EURO VI emission standard. Soon, they are also planning large-capacity forklift trucks with a purely electric drive, which will be powered by photovoltaics on the roof of the new warehouse.

Environmental Responsibility from the Perspective of Breweries

A total of 30 breweries were approached, and ten breweries participated in the survey.

80% of breweries use a circular economy. Brewery 1 and 4 do not use the circular economy for economic reasons. Brewery 1 stated that they are unfamiliar with it as another reason. Since it has been confirmed that at least 80% of breweries in the Czech Republic use some of the circular solutions, we accept hypothesis H0: At least 80% of the breweries in the Czech Republic use some of the circular solutions, and we reject H1: Breweries in the Czech Republic do not use any circular solutions.

Environmental protection is optional for 20% of breweries. Environmental safety is vital for 80% of breweries. These are disturbing results, and it is striking that despite all the demands not only from the European Union, the percentages of importance are not higher.

Other result presents whether breweries are considered an environmentally responsible enterprise. 70% of respondents believe it to be an environmentally accountable brewery, while 30% do not. Although Brewery 1, Brewery 2 and Brewery 10 are not considered environmentally responsible breweries, they still develop at least minimal activities to protect the environment. Brewery 1 sorts waste, Brewery 2 sorts waste, reuses wastewater and does not use single-use plastic barrels but metal. Brewery 10 sorts waste and reduces the energy consumption of machines and buildings.

Brewers´ grain is the final waste after boiling the malt and draining the wort. All surveyed breweries leave the threshed to cattle breeders, who use it as fodder. One brewery uses threshing even more for agricultural production or the production of green energy. It makes crackers from the threshing, yeast and malting waste are also left as feed for cattle, sewage sludge is left to be mixed into the soil as fertiliser, and waste filter diatomaceous earth is used for ploughing and lightening land for reclaimed land. Table No. 1 presents how breweries handle thresh.

Table 1: Brewers´ grain using

	Brewers´ grain using			
	Feeding animals	**Production a snack**	**Production of green energy**	**Agricultural production**
Brewery 1	x			
Brewery 2	x			
Brewery 3	x			
Brewery 4	x			
Brewery 5	x			
Brewery 6	x			
Brewery 7	x			
Brewery 8	x	x	x	x
Brewery 9	x			
Brewery 10	x			

Source: own processing.

Table No. 2 presents what activities breweries develop to achieve environmental responsibility. All breweries sort waste, and two breweries undertake all activities to perform environmental responsibility.

Table 2: Overview of activities to achieve environmental responsibility

Activities to achieve environmental responsibility							
	Waste sorting	**Energy saving**	**Reducing energy consump-tion**	**Wastewater reuse**	**Use of returnable packaging**	**Recupera-tion heat**	**Use of renewable resources**
Brewery 1	x						
Brewery 2	x	x		x	x		
Brewery 3	x	x		x			
Brewery 4	x						
Brewery 5	x	x			x	x	x
Brewery 6	x	x		x			
Brewery 7	x	x	x	x	x	x	x
Brewery 8	x	x	x	x	x	x	x
Brewery 9	x	x	x	x	x		
Brewery 10	x		x		x		

Source: own processing.

Table No. 3 presents the reasons for using the circular economy. Two breweries use circular economy for economic reasons, 3 CE breweries use it for economic and sustainability reasons, and 3 CE breweries use it for sustainability reasons. Brewery 1 and 4 need more motivation. Therefore, they do not use a circular economy. According to the results, we can say that hypothesis H0: Breweries in the Czech Republic have a significant motivation for environmental responsibility, and the introduction of circular measures is accepted, and we reject hypothesis H1: The motivation for environmental responsibility and the introduction of circular measures in breweries in the Czech Republic is low or non-existent.

Table 3: Motivation for circular economy

	Motivation for circular economy	
	Economic reason	**The reason for sustainability**
Brewery 2	x	
Brewery 3	x	
Brewery 5		x
Brewery 6	x	x
Brewery 7	x	x
Brewery 8	x	x
Brewery 9		x
Brewery 10		x

Source: own processing.

Discussion

The first research question, "What circular solutions do breweries in the Czech Republic use in the post-covid era?" can be answered thanks to a survey in which ten breweries participated. Environmental protection is essential to 8 of them. Therefore, they are also considered to be an environmentally responsible company and use a circular economy, except for Brewery 10, which is not considered environmentally responsible. One brewery, Brewery 2, for which environmental protection is not essential, uses a circular economy. Two breweries, Brewery 1 and Brewery 4, which do not use the circular economy, do not use it for economic reasons, and they are too small a business for that; Brewery 1 stated as another reason that they do not know it and further noted that they only sort waste. Therefore, we could accept H0 and reject H1. There is no need for a recommendation to maintain a circular economy because breweries have experienced it and are building a good brand reputation. Brewery 1 and Brewery 4 could invite experts and together come up with a suitable circular measure that would help them economically in the final.

All breweries dispose of waste threshing by providing it to livestock farmers, either free of charge or for a fee. Brewery 3 tried making cookies but soon gave up due to a lack of interest. Brewery 8 stated that they use threshing for agricultural production or the production of green energy, yeast and malting waste serve as feed, sewage sludge is mixed into the soil as fertiliser, and waste filter diatomaceous earth is used for ploughing and lightening the soil for recultivated areas, further from the threshing, in cooperation with an organic bakery, they produce crackers. Here we have comparable results of threshing for cattle as Sehnem et al. (2021) and Terefe et al. (2023).

Other circular solutions consist of the use of wastewater. Brewery 2 also uses water from cooling as utility water. Brewery 3 uses waste hot water to heat water for the next batch. Brewery 6 tries to make 100% use of water; the cooling water is heated during its application and is allowed into the hot water generator. Thus, the water used once is used again; in addition, it is heated to a temperature of around 60° C during cooling, so the heating in the hot water generator water is not so energy-intensive. Brewery 8, thanks to the technology enabling the transformation of slightly polluted water into potable water, can then use the water used for washing new cans, which is polluted somewhat, as service water. Brewery 9 also uses water from cooling to heat the next batch, like Brewery 3. Brewery 10 continues to use the water for utility purposes.

The second research question, "What is the motivation for environmental responsibility and the introduction of circular measures of breweries in the Czech Republic in the post-covid era?" can be answered thanks to the results of the questionnaire processed in Table 3. Breweries 2 and 3 are motivated by purely economic reasons for CE. Breweries 5, 9 and 10 are inspired to CE by sustainability reasons and Breweries 6, 7 and 8 are motivated by both reasons. With these results, we accept H0 and reject H1.

All breweries except Brewery 1 and Brewery 4 save more energy. Brewery 7, Brewery 8, Brewery 9 and Brewery 10 are taking steps to reduce the energy demand of buildings and machinery. Six breweries (Brewery 2, Brewery 5, Brewery 7, Brewery 8, Brewery 9, Brewery 10) use returnable packaging. Three Breweries (Brewery 5, Brewery 7 and Brewery 8) use heat recovery and renewable sources.

Conclusion

This research aimed to identify how breweries in the Czech Republic approach environmental responsibility, whether they apply a circular economy in their operations, and propose procedures for applying or maintaining environmental responsibility. The aim of the research was fulfilled, as it was described here what circular measures the breweries use and how they approach environmental responsibility. Since breweries have been using a circular economy for a long time, they have experienced procedures, they are successful, and in this sphere, they are innovating the techniques themselves. Breweries that do not use circular economy were advised to call in experts for this solution, and together, they could find a suitable solution tailor-made for them.

The answers to the first two research questions show that breweries most often reuse waste water, turn the mash into snacks for people, and are motivated to do so for economic and sustainability reasons.

The limitations of the research lie in the fact that only some breweries participated in the questionnaire survey. Unfortunately, this research was met with the reluctance of brewery representatives to participate in the survey, even though they were offered that the questioning would take place in a form that would suit them.

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Exploring AI in business decision-making

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Abstract

Purpose: The integration of artificial intelligence (AI) into business decision-making processes is a transformative force across industries. This study rigorously analyses recent research to understand the multifaceted nature of AI-enabled decision-making, focusing on ethical considerations, human involvement, AI's impact on business, uncertainty management, AI-human synergy, and methodological improvements.

Design/Methodology/Approach: A systematic literature review was conducted with clear inclusion and exclusion criteria. The search strategy covered various academic databases, and the selected papers underwent rigorous screening. Data extraction and analysis were performed to identify common themes and insights.

Findings: The study reveals key insights into AI-enabled business decision-making. The ethical complexity of AI integration, necessitating transparency, privacy, and robust frameworks is emphasized. AI goes beyond superficial impact, transforming organizations across sectors. Effective uncertainty management and sustainability strategies are crucial. Achieving harmony between AI and human involvement is essential, fostering a comfortable and trusting environment

Originality/Value: This study provides a comprehensive analysis of the multifaceted nature of AI in decision-making, highlighting the importance of ethics, strategic alignment, adaptability, emotional intelligence, and robust research practices.

Keywords: AI-enabled decision-making, Ethical considerations, Human-AI synergy, Business transformation, Uncertainty management, Methodological improvements, Organizational innovation

Introduction

The integration of artificial intelligence (AI) into business decision-making processes has ushered in a profound transformation across various industries (Duan, Edwards & Dwivedi, 2019). In an era characterized by rapid technological advancements and an increasing reliance on data-driven decision-making, this paper aims to shed light on the intricate nature of AI-enabled decision-making. It seeks to unravel the multifaceted implications that this transformative force carries for organizations worldwide, with a particular focus on key themes, including ethical considerations, human involvement, the impact of AI on business value and transformation, uncertainty management, AI-human synergy, and the vital need for methodological enhancements.

Within the context of the digital age, ethical considerations have taken centre stage in the integration of AI into decision-making processes (Harvard Business Publishing Education, n.d.). The emphasis here is on fostering transparency, ensuring privacy preservation, demanding accountability, and establishing trustworthiness. This examination of the complex ethical landscape acknowledges that organizations must tread carefully as they increasingly rely on AI systems to guide their decision-making, necessitating the development of robust ethical frameworks to govern AI utilization.

Moreover, the study recognizes that AI does not operate in isolation but rather in conjunction with human judgment. The study underscores the importance of responsible AI and raises thought-provoking questions about the extent to which organizations are willing to entrust AI with decision-making while acknowledging the fundamental role of humans in the process.

The profound impact of AI extends beyond the surface level and permeates the core of business strategies (Franke, Franke & Riedel, 2022). The study investigates how organizations can strategically align their goals with AI capabilities to drive innovation, create value, and gain a competitive advantage. It delves into the readiness of organizations to embrace this transformative potential in decision-making.

Furthermore, the research navigates the complex territory of uncertainty management in AI-driven decision-making. It underlines the importance of sustainability in AI decision-making and the need for organizations to ensure transparency and accountability while developing mechanisms to navigate unforeseen challenges and sustain AI application over time (Madhavi, Vijay, 2020).

The intricate interplay between AI and human involvement is at the forefront, emphasizing the creation of a harmonious relationship (Thayyib et al., 2023). The study underscores the requirement for a conducive environment that combines technical capabilities with an understanding of human perception and experience.

Lastly, the study addresses the challenges and the pressing need for methodological improvements in AI-enabled decision-making research. It emphasizes the refinement of methodologies and the democratization of AI through frameworks like automated machine learning (AutoML) to address talent shortages and ensure the accessibility and comprehensibility of AI systems.

Methods and Data

Inclusion and Exclusion Criteria

The systematic literature review was conducted with a well-defined set of inclusion and exclusion criteria to ensure the selection of relevant studies that contribute to the understanding of artificial intelligence (AI) in decision-making. The primary objective was to capture a comprehensive view of recent developments in the field, while also filtering out studies that did not directly address the role of AI in decision-making.

Inclusion criteria for this review were as follows: First, papers were required to be directly relevant to the application of artificial intelligence in decision-making processes. Second, to make sure the review covers current advancements in AI research, papers published between 2019 and 2023 were included. Thirdly, scholarly publications, conference proceedings, or peer-reviewed journals were the sources of information.

Papers that failed to satisfy the predetermined criteria were excluded using exclusion criteria. Research that did not primarily centre on the function of AI in decision-making were included in this. Furthermore, articles released prior to 2019 were disregarded due to the possibility that they did not accurately represent the most recent advancements in the field. Ultimately, only English-language papers were taken into consideration for this review due to language limitations.

Search Strategy

For this systematic literature review, finding pertinent papers required a methodical and thorough search strategy. Several academic databases and sources, including both general and subject-specific repositories, were searched by us. The search encompassed the databases ScienceDirect, ACM Digital Library, Web of Science, and Google Scholar.

Search terms and phrases like "artificial intelligence," "decision-making," "business value," "ethics," and "literature review" were utilized to make sure the results of the search were relevant to the review's topic. Many potentially interesting papers were found in the first search.

Data Collection and Screening Process

An organized screening procedure was applied to the original pool of papers. All papers were verified to be unique by identifying and eliminating duplicates. An initial screening of the remaining papers was conducted using their titles and abstracts. In this stage, each paper's applicability to the main theme of AI in decision-making was evaluated. Excluded were any papers that did not closely correspond with the research objectives or did not meet the predetermined criteria.

The complete texts of the chosen papers were acquired and carefully examined after the first screening. At this phase, the papers were given a more thorough assessment to ascertain whether or not they could be included in the systematic literature review. To guarantee that only research directly pertaining to AI's influence on decision-making were included, the inclusion and exclusion criteria were strictly enforced. Nineteen papers that satisfied every requirement were included in the final selection process.

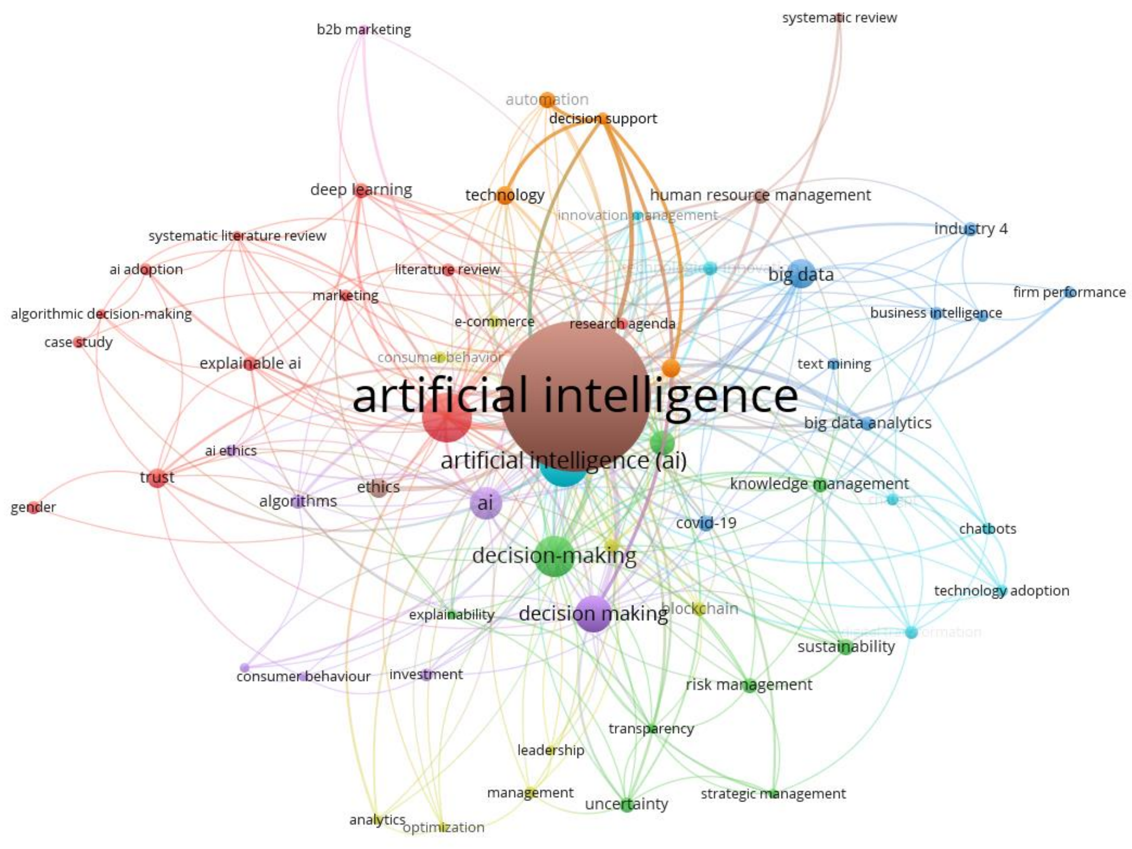
Data Extraction and Analysis

An analysis was conducted on the included papers to extract pertinent information such as the publication year, journal/source, author(s), title, and key findings. To find recurring themes, trends, and revelations about how AI affects decision-making, a thorough synthesis of the data from every paper was done. This analysis helped identify the trends, challenges and opportunities related to AI-driven decision-making by offering a comprehensive summary of the state of the field's research at the moment.

Results

The study used the VoSViewer programme to uncover the deficiencies in research on AI in Business Decision-Making. A search was conducted in the Web of Science database, namely in the categories of Economics, Business, and Management, to explore the relationship between Decision-Making and Artificial Intelligence. The keyword analysis substantiated the theory that there is a requirement for additional publications addressing the relationship between AI and business decision-making.

Figure 1: Results Bibliographic map of Artificial Intelligence



Source: Own

Within the complex network of ideas depicted, "Artificial Intelligence" stands out as a pivotal focal point in the current business decision-making environment. The significance of this centrality highlights the transformative impact of AI in multiple areas of business, ranging from systematic administration to strategies for innovation. Revolved around this central concept are crucial topics such as "big data," "decision-making," and "knowledge management," indicating the fundamental role of AI in handling extensive streams of information and facilitating intricate decision-making processes. The close proximity of nodes associated with "ethics," "trust," and "explainable AI" to the key subject emphasises the significance of transparency and ethical deliberations when firms incorporate AI into their fundamental operations. The connections between "AI," "consumer behaviour," and "e-commerce" highlight the significant influence of this technology on comprehending and forecasting market trends, hence guiding strategic business decisions. Likewise, references to "risk management" and "sustainability" imply that AI can help in dealing with uncertainties and advancing long-term strategic objectives. This visualisation provides a comprehensive overview of the complex and interrelated impacts of AI on business. It suggests that AI is not only a tool but a fundamental component in reshaping company models in response to a quickly changing economic environment.

Study Characteristics

Key findings, publication year, journal/source, author(s), and other pertinent information were methodically extracted from each chosen study. Table 1 provides a thorough reference for every study by displaying the citation information of the 19 papers that were included.

Table 1: List of Included Studies and Their Characteristics

Author(s)	**Title**	**Journal/Source**	**Year**	**Key findings**
Bao, Y., Gong, W., & Yang, K.	A Literature Review of Human–AI Synergy in Decision Making: From the Perspective of Affordance Actualization Theory	Systems	2023	- AI technologies like natural language processing, neural networks, and machine learning play a significant role in enhancing human-AI synergy in decision-making. - AI enables automated information collection and analysis. - AI improves decision-making in various domains. - The paper presents an affordance actualization theory framework.
Duan, Y., Edwards, J. S., & Dwivedi, Y. K.	Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda	International Journal of Information Management	2019	- AI has experienced cycles of development and stagnation, with recent advancements due to Big Data. - Discusses challenges and opportunities in using AI for decision-making. - Offers twelve research propositions for IS researchers, covering conceptual development, AI-human interaction, and implementation.
Enholm, I.M., Papagiannidis, E., Mikalef, P. et al.	Artificial Intelligence and Business Value: a Literature Review	Inf Syst Front	2022	- AI is increasingly important for organizations to create business value and gain a competitive advantage. - Many AI initiatives fail despite substantial investments. - Enablers and inhibitors of AI use are identified, including technological,

				organizational, and environmental factors. - Different use cases for AI are distinguished for internal and external purposes. - The impacts of AI on organizations and competitive performance are discussed.
Franke, F., Franke, S., & Riedel, R.	AI-based improvement of decision-makers' knowledge in production planning and control	IFAC-PapersOnLine	2022	- Presents a methodology to enhance the knowledge of production planners using AI. - Practical testing demonstrated applicability and value for a production company. - Future research focuses on measuring knowledge growth and lean data acquisition. - Aims to understand data's influence on production planning.
Gomes, P. C., Vercosa, L. F., De Melo, F. J. C., Silva, V. F., Bastos-Filho, C. J. A., & Bezerra, B. L. D.	Artificial Intelligence-Based Methods for Business Processes: A Systematic Literature Review	Applied Sciences	2022	- The study reviews AI-based methods used to automate business processes and support decision-making. - It includes a quantitative and qualitative analysis of 21 selected papers. - AI-based methods are used for decision support and business process enhancement, involving techniques like clustering and deep learning.
Gómez-Caicedo, M. I., Gaitán-Ángulo, M., Bacca-Acosta, J., Torres, C. Y. B., & Díaz, J. C.	Business analytics approach to artificial intelligence	Frontiers in Artificial Intelligence	2022	- Business Intelligence combines with emerging technologies for competitive advantages. - Increasing interest in the field with a growing number of publications. - Influence of AI and BA on productive development. - India is the second most productive country in this field. - Topics commonly connected with business analytics include data mining, decision marketing, information systems, big data, and competitive intelligence. - Descriptive analytics is prominent, while predictive and prescriptive analytics need further investigation. - Suggested future research directions include the impact of predictive, prescriptive, and discovery analytics through case studies and the exploration of digital analytics.
Hagendorff, T.	The Ethics of AI Ethics: An Evaluation of Guidelines	Minds and Machines	2020	- AI ethics often fails with limited consequences for deviations. - Reading ethics guidelines have no significant influence on software developers' decision-making. - AI ethics is often considered an extraneous "add-on" in practice. - Economic incentives can override ethical principles. - Ethical aspects related to AI research, development, and application are often omitted in guidelines. - AI ethics should transition from deontological principles to situation-sensitive virtue-based ethics.
Harvard Business Publishing Education	Harvard Business Review	-	n.d.	- AI-powered technologies can improve decision making through real-time tracking, virtual role-play, and generative AI tools. - Real-world examples include Unilever's use of AI to track deforestation in its palm oil supply chain and the Port of Rotterdam's platform for optimizing seaport decisions.

Huang, A. H. and You, H.	Artificial Intelligence in Financial Decision Making	Handbook of Financial Decision Making, Forthcoming	2022	- AI technology has the potential to enhance financial decision-making by converting data into decision-friendly information. - AI applications in finance include NLP, image and voice recognition, and machine learning models for sentiment analysis, earnings and return predictions, and portfolio optimization.
Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A.	Artificial intelligence-based decision-making in accounting and auditing: ethical challenges and normative thinking	Accounting, Auditing & Accountability	2022	- Identified ethical challenges in the use of AI-based accounting systems for decision-making, with a focus on objectivity, privacy, transparency, accountability, and trustworthiness. - Highlighted the importance of human involvement in creating and training AI systems. - Explored ethical decision-making using Rest's four-component model.
Madhavi, M., Vijay, D.	Artificial Intelligence in Business Decision Making	Institute of Scholars (InSc), 2020	-	- AI is not widely known or utilized in India despite its large population. - AI applications in sectors like health, agriculture, and education. - Top AI applications in India include automation, chatbots, NLP, and image recognition. - Urges the need to increase AI adoption in business decision-making in India.
Perifanis, N., & Kitsios, F.	Investigating the Influence of Artificial intelligence on business Value in the digital Era of Strategy: a literature review	Information	2023	- Explored the integration of AI with business and IT strategies as a key enabler of digital transformation alignment. - Identified the synergistic ambidexterity effect of innovative and routine AI deployment, emphasizing its benefits for business value. - Emphasized that AI can reshape the nature of organizations and create new opportunities.
Prasanth, A., Vadakkan, D. J., Surendran, P., & Thomas, B.	Role of artificial intelligence and business decision making	International Journal of Advanced Computer Science and Applications	2023	- Explored the transformative impact of AI on business decision-making, highlighting AI's ability to analyze extensive data and provide precise insights.- Emphasized the need for responsible and transparent use of AI to minimize unforeseen consequences and maintain consumer confidence. - Argued that AI is a valuable tool for making business decisions and is not intended to replace human decision-makers.
Praveenraj, D.D. W., Victor, M., Vennila, C., Alawa-di, A.H., Diyora, P., Vasudevan, N., & Avudaiappan, T.	Exploring explainable artificial intelligence for transparent decision making	E3S Web of Conferences	2023	- Proposal to investigate and apply Explainable AI techniques. - Goals include creating an AI model that explains decisions in understandable terms and assessing efficacy and usability. - Emphasis on the benefits of transparent decision-making.
Ruiz–Real, J. L., Uribe-Toril, J., & Torres, J. A.	Artificial Intelligence in Business and Economics Research: Trends and Future	Journal of Business Economics and Management	2020	- The use of AI in business has garnered increasing scientific attention, especially since 2008. - In terms of AI research, the US, the UK, and China are in the lead. -Numerous academic institutions are supporting AI research, concentrating on various domains. - AI has a big impact on a lot of different industries, like marketing, biotechnology, insurance, and finance. AI is propelling businesses' digital transformation.

Schmitt, M.	Automated machine learning: AI-driven decision making in business analytics	Intelligent Systems with Applications	2023	- The adoption of AI and ML in business analytics has slowed due to a talent shortage brought on by an increase in demand for experts in these fields. -Predictive analytics can be accelerated and the talent gap closed with the aid of autoML frameworks. - The H2O AutoML framework can be a useful tool for user-friendliness, prototyping, and human empowerment even though it cannot achieve complete prediction accuracy.
Steyvers, M., & Kumar, A.	Three challenges for AI-Assisted Decision-Making	Perspectives on Psychological Science	2023	- Limitations like reliance on simulated AIs and low-stakes decision problems must be addressed in empirical research on AI-assisted decision-making. Research on AI-assisted decision-making ought to take into account elements such as cognitive modeling, AI explanation, and human autonomy. - Better performance requires ongoing assessment of AI-assisted decision-making.
Thayyib, P. V., Mamilla, R., Khan, M., Fatima, H., Asim, M., Anwar, I., Shamsudheen, M. K., & Khan, M. A.	State-of-the-Art of artificial intelligence and big data analytics reviews in five different domains: A bibliometric summary	Sustainability	2023	- Business intelligence and analytics are crucial in modern organizations. - AI has the potential to disrupt various aspects of society. - AI plays a role in sustainable business models and marketing. - Big Data and AI applications in finance have been increasing. - AI applications in education need more research and integration. - Various clusters of AI and Big Data research identified in different domains.
Torre, C., Guazzo, G. M., Çekani, V., & Bacco, V.	The Relationship between Big Data and Decision Making. A Systematic Literature Review	Journal of Service Science and Management	2022	- Big data can facilitate corporate decision-making in both private and public sectors. - The use of advanced tools and technologies can enhance decision-making by providing useful information. - Levers that impact decision-making effectiveness include efficiency, timeliness, precision, and effectiveness.

Source: Own

Risk of Bias Within Studies

Assessments of the risk of bias within individual studies were not explicitly addressed in the selected papers. The majority of the included studies were literature reviews and empirical research articles that did not present a specific risk of bias assessment for their content. As a result, there was limited data available for evaluating the internal validity of each study or assessing potential biases.

Results of Individual Studies

The outcomes in these studies were primarily qualitative in nature and did not involve specific interventions or quantifiable effect estimates. Therefore, the presentation of simple summary data, effect estimates, and confidence intervals, as recommended in PRISMA for intervention-based studies, was not applicable to the selected literature.

Synthesis of Results

The synthesis of results was based on a thematic analysis of the included papers. Common themes, patterns, and insights related to the role of artificial intelligence in decision-making across various domains were identified. Due to the qualitative nature of the findings and the absence of quantifiable outcome measures, no meta-analyses were conducted. As a result, there were no confidence intervals or measures of consistency to present.

Risk of Bias Across Studies

An assessment of the risk of bias across studies was not explicitly performed in this literature review. The selected papers encompassed a diverse range of research, and the absence of standardized methodologies across all studies limited the ability to conduct a comprehensive assessment of bias across the literature.

Additional Analysis

No additional analyses, such as sensitivity or subgroup analyses, or meta-regression, were conducted as part of this literature review. The selected papers were primarily reviewed for their individual contributions to the field of artificial intelligence in decision-making and were not subjected to further statistical or methodological analysis.

Discussion

Ethical Considerations and Human Involvement

The ethical dimensions surrounding AI in business decision-making are far from trivial; they are central and intricately complex. Lehner et al. (2022) research embarks on a comprehensive exploration of the ethical challenges surrounding AI-based decision-making. Their study exposes the tip of the iceberg, emphasizing the ethical intricacy of integrating AI into business decisions. Objectivity, privacy preservation, transparency, accountability, and trustworthiness are highlighted as pivotal ethical touchpoints. Their findings shed light on the ethical tightrope organizations must traverse as they integrate AI systems into their decision-making processes.

This study serves as a stark reminder that the integration of AI into decision-making processes is not merely a technical exercise; it entails navigating intricate and often conflicting ethical dimensions. It becomes evident that the ethical adoption of AI in decision-making hinges on transparency, privacy preservation, and establishing mechanisms for accountability. The core message here is that AI-enabled decision-making is a delicate ethical dance, demanding the establishment of robust ethical frameworks to govern AI utilization.

Furthermore, the study by Lehner et al. (2022) boldly underscores the indispensable role of human involvement in the development and training of AI systems. This aligns squarely with the concept of responsible AI, a concept in which AI operates not in isolation but in tandem with human judgment. This perspective is reinforced by Prasanth et al. (2023), who also underline the pressing need for responsible and transparent AI use in decision-making. The critical question posed here is whether organizations are ready to relinquish complete control to AI, or whether they recognize that the heart of decision-making remains firmly grounded in human judgment.

Hagendorff (2020) critically evaluates AI ethics guidelines and their effectiveness. The findings reveal that AI ethics guidelines often fail to have a significant influence on software developers' decision-making. Ethical principles may be perceived as an extraneous "add-on" in practice, particularly when economic incentives compete with ethical considerations.

This critique emphasizes the ongoing challenge of translating ethical principles into practical and effective guidelines for AI decision-making. It underscores the need to transition from deontological principles to situation-sensitive virtue-based ethics. Furthermore, it raises questions about the role of stakeholders in reinforcing ethical norms within AI systems and processes.

Praveenraj et al. (2023) study on Explainable AI techniques aligns with the critical discussions about transparency, trust, and accountability in AI decision-making. Their methodology highlights the need to make AI models and decisions understandable, reinforcing the importance of explain ability.

From a critical perspective, this discussion raises questions about the practicality of implementing explainable AI in complex decision-making processes. It prompts considerations about the balance between transparency and the need for AI systems to handle vast and intricate data.

The interconnection between these studies raises questions about the precise balance between AI automation and human involvement in decision-making processes. It underscores that ethical AI-enabled decision-making is not a matter of merely following regulations and guidelines but rather an intricate fusion of human judgment, ethical principles, and technological innovation. The discussion extends to the idea that ethical principles should not be confined to paper; they must be ingrained within AI models and decision-making processes, fostering a responsible and trustworthy AI ecosystem.

AI's Impact on Business Value and Transformation

The impact of AI on business decision-making transcends the superficial; it delves into the essence of organizational transformation. Perifanis and Kitsios (2023) conducted an extensive literature review to unveil the transformative role of AI in aligning business strategies. Their argument is bold and unambiguous: AI serves as a catalyst for reshaping organizations and unlocking novel opportunities. This is a theme that has reverberations throughout the business landscape, heralding a new era in business strategy.

The research of Bao et al. (2023) strengthens this theme even more. Their results highlight how important artificial intelligence is to improving decision-making in a variety of fields. Although evident, this interrelationship between the studies also poses some concerns. How ready are businesses to accept this profound change in how they make decisions, and how well-positioned are they to take advantage of AI's revolutionary potential?

The research done by Ruiz-Real et al. (2020) and Enholm et al. (2021) provides insight into the rising interest among academics in the use of AI in business. They draw attention to AI's capacity to spur digital transformation and have an impact on a number of industries, including marketing, biotechnology, insurance, and finance.

Analytics and business intelligence are changing, as demonstrated by the study by Gómez-Caicedo et al. (2022). Data mining, decision marketing, information systems, big data, and competitive intelligence are among the fields where they see growing interest.

The importance of big data in supporting business decision-making in the public and private sectors is emphasized in Torre et al.'s systematic literature review (2022). The authors offer valuable perspectives on strategies for managing uncertainty and emphasize the significance of upholding sustainability in AI-based decision-making.

A comprehensive examination of AI-based methods to support decision-making and automate business processes can be found in the study by Gomes et al. (2022). A quantitative and qualitative analysis of 21 selected papers is provided by means of a methodical examination of relevant literature and keyword co-occurrence analysis.

This approach is exacting and offers a strong basis for comprehending the current state of artificial intelligence as it relates to process automation. It acknowledges the value of AI methods like deep learning and clustering in improving decision support systems.

The potential of AI applications in financial decision-making is highlighted in Huang and You's (2022) study. These applications include sentiment analysis, earnings and return forecasts, portfolio optimization, image and speech recognition, and machine learning models.

The need for strategic AI integration is becoming more and more obvious; it is no longer just an option. This discussion highlights the idea that companies should use AI as a strategic pillar that is deeply ingrained in their operational DNA, rather than just implementing it as a new technology. An agile mindset, proactive planning, and strategic foresight are essential in the age of AI-driven transformation. Businesses must now integrate AI capabilities with their business objectives to create a harmonious blend of innovation, value creation, and competitive advantage.

Uncertainty Management and Sustainability

The spectre of uncertainty haunts every decision-making process, and AI introduces a novel dimension to managing this uncertainty. Wu, Shang (2020) research provide essential insights into managing uncertainty in AI-enabled decision-making. They propose mechanisms for effectively dealing with unpredictability and stress the importance of maintaining sustainability in AI decision-making. Their focus on sustainability echoes the ethical considerations highlighted by Lehner et al., (2022) extending the conversation to the broader context of ethical AI deployment.

This theme has significant depth. It underscores that sustainability in AI-enabled decision-making necessitates robust strategies for risk mitigation and adaptability in the face of unexpected events. The organizational implication is that businesses must not only ensure transparency and accountability in AI decision-making but also establish mechanisms for dealing with uncertainty and a plan for the sustained application of AI over time. The long-term success of AI-enabled decision-making hinges on the ability to navigate and overcome unforeseen challenges.

AI and Human Synergy

The study by Yu, Li (2022) explores the subtle nuances of AI-human synergy, where AI decision-making transparency, effectiveness, discomfort, and trust intersect in a complex web. These findings echo the message conveyed by Prasanth et al. (2023), who recognize the value of AI as a tool to enhance decision-making without supplanting human decision-makers. The in-depth analysis here is that AI-human synergy is not a matter of technology alone but a complex dance involving perception, experience, and trust.

The crux of the matter is that creating a harmonious AI-human relationship is not solely reliant on the technical capabilities of AI; it is deeply entwined with how AI systems are perceived and experienced by employees. The inference is that for AI to be embraced as a valuable ally in decision-making, organizations must foster a comfortable and trusting environment. The discussion here raises questions about the emotional quotient of AI, suggesting that successful AI integration necessitates a user-centric approach that delves into the nuanced human psyche.

Challenges and Methodological Improvements

The trajectory of AI-enabled decision-making hinges on rigorous methodologies and research practices. Steyvers, Kumar (2023) cast a critical spotlight on the limitations of existing empirical research in AI-assisted decision-making. They emphasize the need for continual evaluation and methodological improvements. This theme of addressing challenges and improving research methodologies is interwoven with Schmitt (2023) study, which highlights the talent shortage in AI/ML and suggests automated machine learning (AutoML) as a pragmatic solution.

The pivotal role of methodological advancements in AI-enabled decision-making research is underscored. This entails refining data quality, delving deeper into the intricacies of human behaviour, and the continual evolution of research processes. Furthermore, the discussion extends to the heart of democratizing AI capabilities within organizations. The democratization of AI, notably through AutoML frameworks, becomes a pressing necessity for organizations to adapt to the talent shortage and ensure the accessibility and comprehensibility of AI systems.

Conclusion

In the course of the study the multifaceted landscape of AI-enabled business decision-making is traversed, uncovering a profound and intricate tapestry of insights that will undoubtedly shape the future of organizations in a technologically driven world. The integration of artificial intelligence into decision-making processes has indeed proven to be a transformative force across various industries, challenging us to comprehend its profound implications while navigating a complex web of ethical considerations, human involvement, business transformation, uncertainty management, AI-human synergy, and methodological advancements.

Ethical considerations have emerged as a central and intricate facet of AI adoption, demanding transparency, privacy preservation, accountability, and trustworthiness. The papers we've examined emphasize the ethical tightrope organizations must walk as they integrate AI into decision-making, underscoring the necessity of establishing robust ethical frameworks to govern AI utilization. The implication is clear: the adoption of AI in decision-making is not a mere technical exercise; it is a complex and ethical endeavour, one that carries a moral responsibility that organizations must take seriously.

Human involvement remains at the core of decision-making, even in the era of AI. The importance of responsible AI, where human judgment and AI operate in tandem, cannot be overstated. It raises essential questions about the extent to which organizations are willing to cede control to AI while preserving the critical role of human judgment. The harmonious interplay of AI and human involvement becomes paramount in fostering a comfortable and trusting environment in which AI can thrive.

AI's impact on business value and transformation transcends the superficial. AI serves as a catalyst for reshaping organizations and unlocking novel opportunities. It underscores that organizations must not merely adopt AI as a technical novelty but strategically align their business goals with AI capabilities, creating a symphony of innovation, value creation, and competitive advantage.

The spectre of uncertainty in decision-making introduces a novel dimension with the advent of AI. Managing unpredictability is essential, as highlighted in our exploration, and maintaining sustainability in AI decision-making is crucial. It underlines that businesses must not only ensure transparency and accountability in AI decision-making but also establish mechanisms for dealing with uncertainty and a plan for the sustained application of AI over time.

The intricate interplay of AI and human involvement is not solely reliant on technical capabilities but delves into the emotional quotient of AI. The success of AI-human synergy depends on fostering a comfortable and trusting environment, acknowledging that AI is not just a tool but a complex interplay of perception, experience, and trust.

Challenges and the need for methodological improvements in AI-enabled decision-making research have been highlighted. Refining research practices and methodologies is pivotal to the trajectory of AI adoption. Furthermore, the democratization of AI, notably through frameworks like automated machine learning (AutoML), becomes a necessity for organizations to address the talent shortage and ensure accessibility and comprehensibility of AI systems.

In conclusion, organizations that effectively navigate this complex landscape will be best poised to unlock the full potential of AI in their decision-making processes, fostering innovation, growth, and responsible practices in the dynamic realm of AI-enabled business decision-making. As we stand at the precipice of a new era in decision-making, it is imperative that organizations heed these insights and embark on the path of responsible and innovative AI adoption.

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Development of the price of selected metals used in the circular economy

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Abstract

The article aims to identify the development of the prices of steel, copper, silver and gold used in the circular economy. The monitored period is 2009-2023. For clarity, the monthly price development on world stock exchanges is used. The time horizon 2009-2023 is divided into three described periods. The economic crisis of 2009-2010, the COVID-19 pandemic in 2020-2021 and the Russian invasion of Ukraine in 2022-2023. The average price and mean for each metal in the observed period are always used for better clarity. During this time, the price of copper, gold and silver rose, while the price of steel tended to fall. Gold and silver rise because they are seen as a haven for investment, so their price rises in times of uncertainty. Furthermore, there is an increase in the demand for electronics, which increases the price of copper even during crisis periods. Adverse effects on the economy mainly cause a drop in the price of steel, as its consumption has mostly stayed the same in recent years. The prices of selected metals are essential because they influence the prices of goods, and we can also observe the current development of the world economy on them.

Keywords: Economic crisis, COVID-19 pandemic, Russia-Ukraine conflict, price developments, metal commodities

Introduction

The development of the price of metals is significant for the circular economy because metals are easily recycled (Horák, Machová & Krulický, 2019). At the same time, they are essential, especially in the production of electronics and the construction industry. We will monitor the development of steel, copper, gold and silver prices. The prices of these commodities depend on the prices on the stock exchange (Machová, Krulický & Horák, 2020).

Among the most commonly used metals is steel. This metal is a typical long-term successful illustration of the circular economy (Horák, Pavlová, 2022). Recycling has been a part of steel production since the beginning of its production. The price depends on scrap and the "new" steel itself. At the same time, due to constant high demand, there are frequent price increases (Fischer, 2021).

Another frequently used metal is copper. It is used to manufacture pipes and electronics. Because copper is easy to process, it was used in ancient times and recycled here for the first time (Bartoš, Vochozka & Šanderová, 2022). The price of copper is essential for producers' plans and for its forecast; for example, a three-factor stochastic model is used, which uses the forecasts of the Bloomberg agency, as well as the COMEX and LME exchanges (Cifuentes et al., 2020).

The most frequently mentioned metals are gold and silver. These raw materials were previously used mainly for producing jewellery, coins and various decorative items. Currently, however, they have found another use: electronics production. They are easy to process, and their recycling has been common since the beginning of their processing times (Horák, Dušek, 2022). However, compared to copper and steel, the development of their prices is also influenced by the fact that gold and silver are considered investment metals (Sadorsky, 2021). During various crises in the market, there is an increased demand for these metals and a subsequent increase in the price. Therefore, in their predictions, the manufacturer must consider difficult-to-predict price fluctuations in the market (Baur, Beckmann & Czudaj, 2020). Apergis, Apergis (2019) used an empirical analysis that uses the ARDL model and combined cointegration to estimate the price of silver. The goal of combining these methods is to express the relationship between the production of solar panels and the price of silver.

An effort to find the best method to predict the three most essential metals in the market - gold, silver and copper - appeared in 2017 by Kristjanpoller, Hernández (2017). ANN-GARCH model with regressors was the best model for forecasting the price return volatility of these significant metals. Due to the heteroskedasticity of the financial series, the loss function HMSE (Heteroskedasticity-adjusted Mean Squared Error) is used, and the Confidence Set model is used to test the superiority of the models.

Nowadays, when all sectors of the economy are heavily influenced by the circumstances that have happened or are still happening, it is appropriate to determine to what extent these circumstances affect the metal markets. Looking back not too far, we can see the economic crisis and uncertainty related to the COVID-19 pandemic (Rydell, Šuleř, 2021). We have been dealing with the Russian-Ukrainian conflict for over a year, affecting us all, not only beyond the borders. It is a question of how these events affect metal prices and their development. To this day, understanding the impact of an infectious disease pandemic on stock market volatility is of great concern to investors and policymakers (Bai et al., 2021), especially after the recent experience each of us, which persists in certain parts of the world. Research from 2020 in Vietnam shows significant changes, especially in the financial sector and stock markets, which showed opposite values than expected (Anh, Gan, 2020). After the outbreak of war in Ukraine, companies and countries had to adapt their activities to the consequences of this conflict strongly (Matasova, Vochozka & Rowland, 2022). It shows that the European financial system is still fragile to external shocks, which can be seen in the result of research showing that after the outbreak of the war in Ukraine, the value of the euro was devalued in correlation with the exchange rate to the ruble (Aliu Hašková & Bajra, 2023).

The thesis aims to identify the development of the prices of steel, copper, silver and gold used in the circular economy. The monitored period will be 2009-2023. To achieve this goal, the following research questions are defined:

RQ1: How did the economic crisis in 2009 affect metal prices?

RQ2: How did the COVID-19 pandemic affect the development of metal prices?

RQ3: How did the Russian invasion of Ukraine affect the price of metals?

Metal commodities are used as investments in industry and other sectors. An example can be steel, which is mainly used in the engineering industry, for the production of car bodies, but also in the construction industry, where it is primarily used as reinforcement for concrete structures. The largest producers and consumers of steel are located in China. Therefore, the development of steel prices is highly dependent on prices in this country. Ma (2021) used the analysis of iron ore prices, carbon emission allowances, and shipping to predict the price. Specifically, they analyzed price spillovers, dependency structure and spillover risk between iron ore, steel scrap and carbon dioxide emission allowances. The authors' results show that since China's policy to reduce excess capacities in steel production, Chinese prices are mainly subject to iron ore prices. To forecast steel prices in the Czech Republic, Zapletal, Chytilová (2016) used a method that can also be used in other EU member countries. Here, companies are under the influence of carbon trading, which can be an advantage on the one hand, but rather a threat on the other. The method focuses on assessing the effectiveness of steel companies' emissions management and examines the influence of two critical factors of this process. These are emission prices and banking options (transfer of unused allowances to the following period). According to Saniuk, Saniuk (2018), Industry 4.0 technology, which is attracting more and more attention worldwide, can also be used to determine the global price of steel in the future. These new technologies are intended to increase efficiency and performance. Also, this method identifies the main benefits and threats resulting from introducing the Industry 4.0 concept. Much research is emerging in the framework of reuse in steel production. Lupu et al. (2021) comment on how the current legislation requires the search for solutions for converting wastes stored or generated during current production flows into by-products that can be used in industry. It also represents the possibility of increasing the capacity of small and powdered iron wastes generated in the steel industry by converting them into by-products in agglomerate. Similarly, Budiul & Berghian (2021) research investigated the use of iron sludge generated in the steel industry in the context of a circular economy.

Copper is also widely used in industry to produce electronics or pipes. Also, in the case of copper, China is the largest exporter; we assume that international copper price shocks affect China's producer price index (PPI). When testing this method, Wen, Zhao & Hu (2019) used a time-varying parametric structural vector autoregression model with stochastic volatility to analyze the impact of a copper price shock, which is divided into a supply shock, an aggregate demand shock, and a specific copper demand shock. The results show that the impact of international shocks on China's PPI is time-varying. Price shocks significantly affect PPI in the short and medium term, and the aggregate demand shock is the most pronounced. Another interesting method of determining the price of copper was used by Ardente, Beylot & Zampor (2023) when they addressed the degree of damage to sources of this metal. The authors used this method for conditions in the EU. He states that 90% of the loss in value is due to poor final disposal of tailings, not to mention the environmental impact. A system that tries to effectively and accurately predict the development of the copper price was developed by Liu et al. (2017). They used a machine learning algorithm based on a decision tree. This method can accurately and reliably predict copper prices in both the short-term (days) and long-term (years), with an average absolute percentage error of less than 4%. Furthermore, the method is assumption-free, robust, and not susceptible to human bias. This method is quickly and effectively used to forecast the prices of other metals and other commodities. Even Khoshalan et al. (2021) recognize that metal price is one of the most critical and influential parameters in assessing various projects such as industry and mining. In this regard, price changes can play a vital role in the correct decision-making by managers on the development or limitation of mining activities. Khoshalan et al. (2021) used gene expression programming (GEP), artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS) and ANFIS-ACO (ant colony optimization algorithm) to predict copper price. In this study, the ANN model was selected as the best model for predicting copper prices, but overall, all the mentioned methods were acceptable. The development of the price of copper from 1959 to 2022 was addressed by Vochozka et al. (2021). They focused on the forecast of development in 2022 and analyzed the impact of the COVID-19 pandemic on this commodity. Citing increasing demand after the outbreak of the pandemic and reporting an accelerated trend, daily historical closing prices of copper from the COMEX commodity exchange were analyzed into a time series, which was then processed by artificial intelligence using neural networks. Vochozka et al. (2021) propose, taking into account the limits of the work, its improvement – an effective combination of traditional methods with advanced artificial intelligence techniques.

Other metals important for the circular economy include silver, which is used in producing photovoltaic panels but is also considered an important investment metal (Brabenec et al., 2020). An interesting method for determining the price of silver was proposed by Phitthayanon, Rungreunganun (2019). This method is interesting because it examines price developments for small jewellery manufacturing businesses in Thailand. This method relies on historical price data since small companies cannot access relevant oil prices and other economic data. This model can provide an RMSE (root mean square deviation) prediction of 0.00765, comparable to other methods. The advantage of this prediction is mainly in the simplicity of the model, and a large amount of data is unnecessary. Another approach to determining the price of silver was using a mathematical method devised by Korotkov, Korotkova (2017). The approach aims to detect latent periodicity in the presence of deletions or insertions in the analyzed data if the omissions or insertions' sites are unknown. The developed method uses dynamic programming and random matrices. It can also be used to determine the price of silver and gold, company shares or stock market indices.

Similar to silver, gold is used not only for production but also for investment. The price of gold is very susceptible to crises in the world. Baur (2013) also found that gold is subject to the so-called "underground effect". This effect lies in statistics that show that in September and November, the price of gold achieves positive and statistically significant changes every year. Baur (2013) explains this anomaly by investors' hedging demand in anticipation of the "Halloween effect" in the stock market, demand for gold jewellery during the wedding season in India, and negative investor sentiment due to the shorter summer time. Bentes Gubareva, Teplova (2022) also confirmed the existence of the autumn effect. During the COVID-19 pandemic, this autumn effect's disappearance and subsequent reverse behaviour were noted (November 2020). On the contrary, the unusual behaviour of gold volatility and seasonal effects were not identified. The results also confirm the positive asymmetric impact of gold fluctuations. Baur, Beckmann & Czudaj (2020) tried to evaluate whether the price of gold is overvalued or undervalued. So, they analyzed gold prices concerning commodity prices, consumer prices, stock prices, dividends and bond yields. The authors prove that when there is an increase in market confidence, the relative price decreases, while in the case of increasing distrust, the relative price increases. Immanuvel, Lazar (2020) sought to determine how the arrival of information in the market affects gold prices. They analyzed information spillovers and leverage transferred from countries that are the largest consumers of gold. A multivariate exponential generalized autoregressive conditional heteroskedasticity model was used here. Research has shown that price movements are significantly influenced by information from India and the US. Immanuvel, Lazar (2022) also conducted another follow-up research showing that although India is the largest gold market in the world, it takes prices from other world exchanges, such as the London Stock Exchange. The authors suggested that Indian gold bullion producers take initiatives that would enable India to become a global gold price maker.

Methods and Data

The development of stock exchange prices will be used, from which the prices of contracts concluded outside the stock exchange also depend. The data will be drawn from the website tradingeconomics.com, which publishes the development of price indices. First, the time series of data from 2009 to 2010, when the economic crisis affected the price of commodities, will be described. Next, data from 2020 to 2021, when the COVID-19 pandemic hit the world, will be examined. The next examined period will be 2022 to 2023 when the Russian invasion of Ukraine began. To compare the price development in these periods, formulas will be used to calculate the average price (formula number 1), which is given in Chinese yuan per ton for steel, dollars per pound for copper, and dollars per ounce for silver and gold.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (1)$$

Furthermore, the formula for calculating the mean (formula number 2) will be used here, which is not distorted by extreme values compared to the average and better expresses the mean value during the monitored period. Prices will again be quoted for steel in Chinese yuan per ton, copper in dollars per pound, and silver and gold again in dollars per ounce.

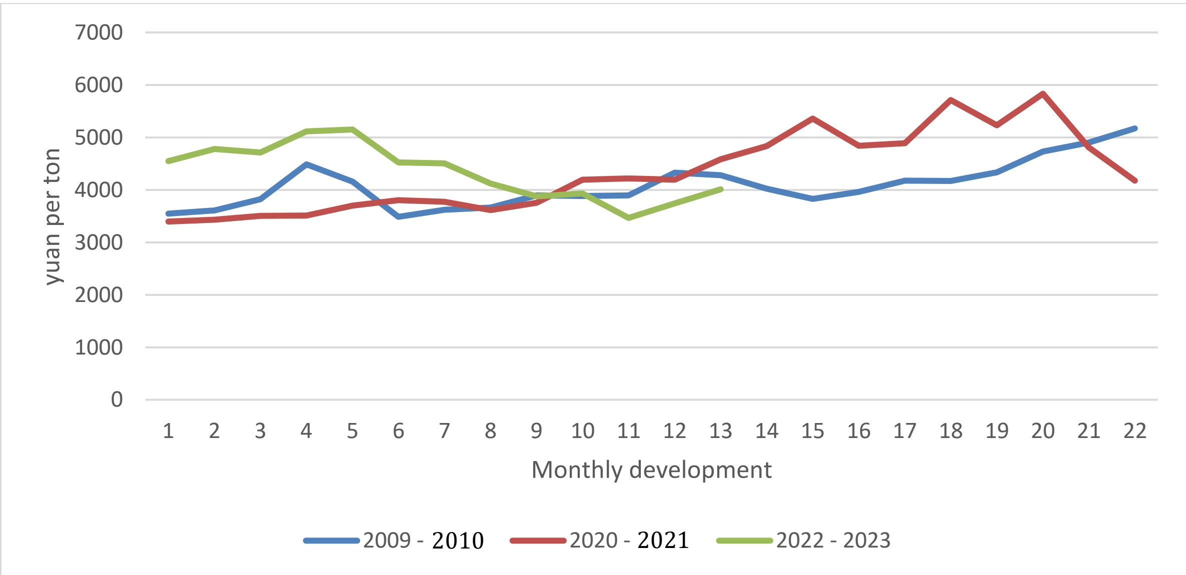
$$\mathrm{ME(X)} = x_{(N+1)/2} \tag{2}$$

Therefore, the primary method used for the research will be the analysis of the time series of the development of the prices of steel, copper, silver and gold. Price indexes from the already described years and events that impacted the development of these indexes will be used. These events are the economic crisis from 2009 to 2010, the COVID-19 pandemic from 2020 to 2021 and the war in Ukraine, which directly followed the pandemic from 2022 to 2023. Using Excel, tables and graphs will be created to describe the findings as results. Monthly data will be used for each metal in the given periods. It will be interesting to see how quickly the market reacts to information shocks and how much the price of the monitored metals will rise or fall. Thus, the comparison method will be used to monitor the differences and fluctuations in the time series of individual tracked metal commodities.

Results

The data comes from tradingeconomics.com, which records price developments in stock markets. Graph 1 shows the prices in individual months so that we can easily observe the effect of prices. Each chart shows data from 2009 to 2010 when the economic crisis affected the markets. Next, data from 2020 to 2021, when the COVID-19 pandemic took place, and data from 2022 to 2023, when the Russian invasion of Ukraine affected the markets.

Graph 1: Steel price development



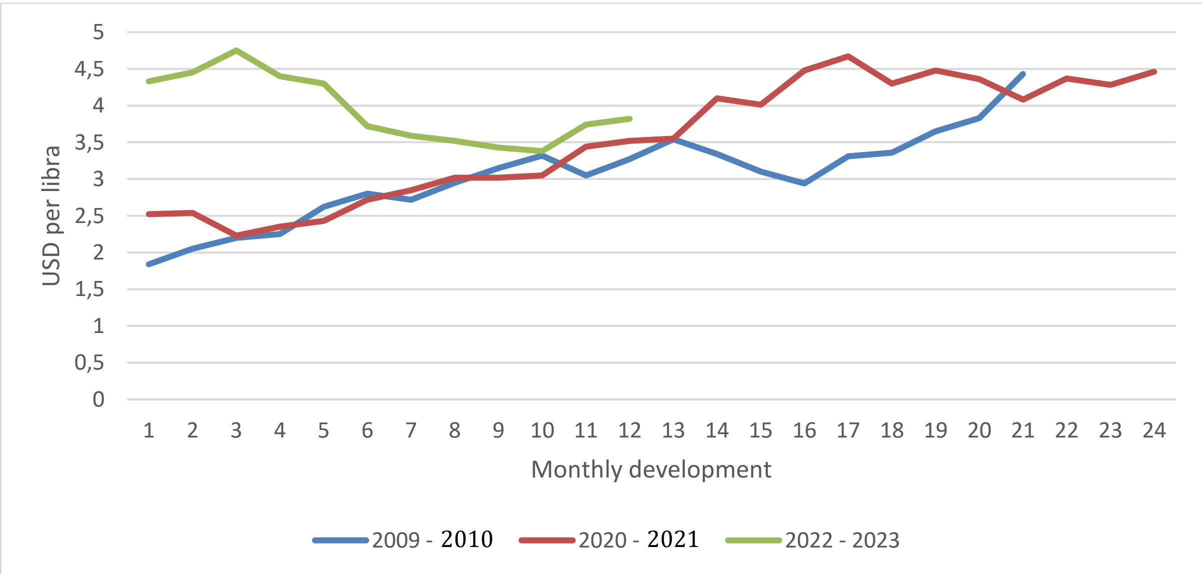
Source: Author.

First, we describe the data from 2009 to 2010, which includes prices in 22 months. At the beginning of this period, it can be seen from the development of the curve that there was an optimistic mood in the markets between the 4th and 5th months, but this mood did not last long, and steel prices returned to prices around 3600 yuan per ton. A more permanent increase in steel prices occurred until the end of the economic crisis in 2010. Here, steel prices reached values of 5000 yuan per ton. The average price during this period was 4088.64 yuan per ton, and the mean was $3992.5 per ton of steel.

The following data will be from 2020 to 2021; the graph shows prices for 22 months. It is interesting here that since the steel demand has decreased due to the pandemic, at the same time, steel mills have been closing, especially in China, which is the largest producer, and the price of steel has stabilised at around 3,700 yuan per ton. At the beginning of 2021, the price rose to a value of 5,500 yuan per ton, but due to the re-closure of large cities in China, there was a drop again to a value of around 4,000 yuan per ton. Average steel prices during this period were $4341.81 per ton, and the mean was $4192 per ton.

The following data is from 2022 to 2023; data from 13 months was used here. The data from 2022 shows that steel prices were relatively stable. They were around 5,000 yuan per ton. This relative stabilisation was also due to the impact of COVID-19, as the widespread closures in China were lifted, which caused the economy's relaunch. However, towards the end of 2022 and the beginning of 2023, the uncertainty in the markets caused by the Russian invasion took full effect, and steel prices fell to values of 3500 yuan per dollar. The observed prices during this period averaged 4,345 yuan per ton, and the mean value was 4,504 yuan per ton of steel. See Graph No. 2.

Graph 2: Cooper price development



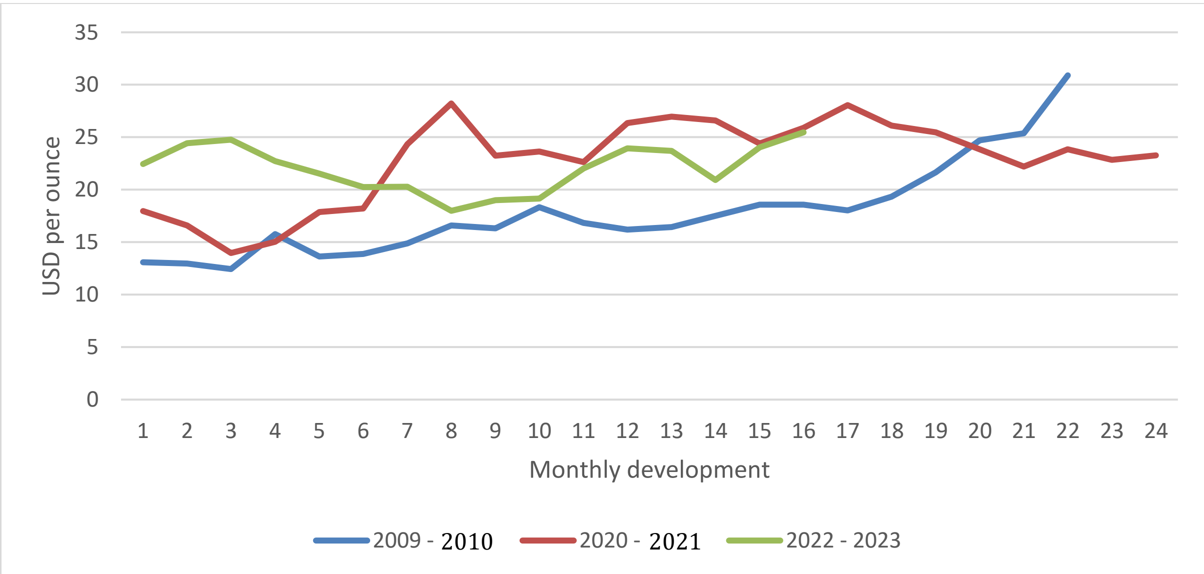
Source: Author.

First, we will describe the data from 2009 to 2010. During this period, we are monitoring data for 22 months. What is interesting about these data is that although the economic crisis affected the markets, the price of copper more than doubled during this period, namely from a value of 1.84 dollars per pound to a value of almost 4.5 dollars per pound. The average price during this period was $3.03 per pound, and the mean was $3.1 per pound of copper.

The following monitored data is from 2020 to 2021; we are tracking the price development in 24 months. During this, despite the COVID-19 pandemic, the price of this metal rose again. This growth was mainly due to increased demand for electronics. Since copper is one of the essential production metals in electronics, there has been an increase in the market for this metal. The already mentioned COVID-19 closures in China also impacted the price increase because China, like steel, is the largest copper processor in the world. The average price during this period was $3.53 per pound, and the mean was also $3.53 per pound of copper.

Next, we monitor the data from 2022 to 2023 (see Graph No. 3), and the graph's curve expresses the price development in 12 months. Here, the price of copper fell from $4.75 per pound to $3.38 per pound. This decline was caused by the uncertainty in the markets caused by the war in Ukraine. However, it was not the only factor. Furthermore, there was a decrease in the demand for electronics, and, as I already mentioned, this also harmed the demand for copper. The average price of copper during this period was $3.95 per pound, and the mean was $3.78 per pound of copper.

Graph 3: Silver price development



Source: Author.

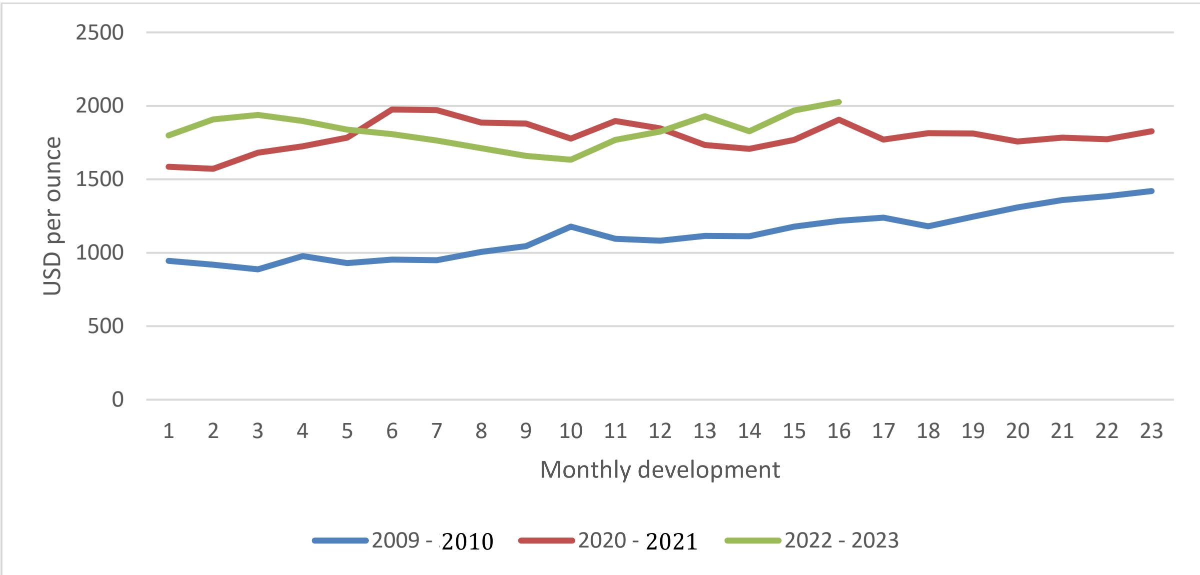
Again, we will first describe the data from 2009 to 2010, the time horizon of the monitored period is 22 months. This data shows that silver is often used as an investment metal in times of crisis. As a result of the economic crisis, there was a steady increase in the price of silver.

And that from values around 13 dollars per ounce to 30 dollars per ounce. The average price during this period was $17.82 per ounce, and the mean was $16.73 per ounce of silver.

Next, data from 2020 to 2021 are described, data for 24 months is used here. The price development in this period was very turbulent. Due to market uncertainty caused by COVID-19, the price dropped from $17.96 per ounce to $13.97 per ounce at the beginning of this period. However, silver's safe-haven nature became apparent after that, and values rose to $28 per ounce. Towards the end of this period, at the end of 2021, the markets gradually calmed down, and the price of silver stabilized at around $22 per ounce. The average price during this period was $22.81 per ounce, and the mean was $23.74 per ounce of silver.

Between 2022 and 2023, the price of silver fluctuated again, for better clarity, the data for 16 months are shown here. This swing occurred between 2022 and 2023. This dip occurred due to the uncertainty caused by the invasion of Ukraine, and at the same time, there was a decrease in the demand for electronics. Since silver is an essential metal in electronics production, this factor again harmed the price of silver. However, at the beginning of 2023, uncertainty prevailed in the markets again, and prices were renewed up to values of $25 per ounce. The average price during this period was $22.05 per ounce, and the mean was $22.24 per ounce of silver. Graph 4 closely follows the development of the gold price for the given periods.

Graph 4: Gold price development



Source: Author.

Again, we will first start with the development of the data in the period 2009 to 2010, the presented development shows the prices for 23 months. Here again, as with silver, confidence in gold was shown. Again, this metal is therefore considered a safe harbour in times of crisis. We can see the price rise here throughout this period. Prices here ranged from $943.98 per ounce to $1,419.9 per ounce. The average price during this period was $1118.62 per ounce, and the mean was $1112.6 per ounce of gold.

The next period described is again from 2020 to 2021, and the curve of the graph shows the prices in 23 months of this period. Here again, due to the market crisis and the pandemic, the price of gold rose. The initial price in this period was $1,584 per ounce, and at the end of this period, the price was $1,828 per ounce of gold. However, there was no permanent price increase as in the previous monitored period. During 2021, the uncertainty in the markets was higher, and gold prices jumped to 2000 dollars per ounce. Prices fell to $1,828 an ounce due to the positive sentiment in the markets caused by the end of the pandemic. The average price during this period was $1,792.37 per ounce, and the mean was $1,782.5 per ounce.

The last monitored period is 2022 to 2023, for better clarity, the development in 16 months is shown here again. Interestingly, at the beginning of this period, the price of gold reached almost 2000 dollars per ounce due to the Russian invasion of Ukraine. However, as with silver, gold is an essential metal in the production of electronics, and again due to the decline in demand for electronics, the price of gold has fallen at the end of 2022 to $1,633 per ounce. But then uncertainty prevailed on the markets again, and the price rose to values of $2,000 per ounce. The average price during this period was $1,831.16 per ounce, and the mean was $1,826.4 per ounce of gold.

Discussion

RQ1: How did the economic crisis of 2009 affect metal prices?

During the economic crisis, the price of steel fell to 3,600 yuan per ton due to reduced demand and market uncertainty. Prices could overcome these problems only with the end of the economic crisis in 2010 when prices reached 5000 yuan per ton of steel. However, the prices of copper, silver and gold developed differently. Interestingly, there was a steady growth in these metals between 2009 and 2010. For gold and silver, this growth was due to these metals being taken as safe havens in times of crisis. In this period, the price of gold went from 950 dollars per ounce to 1400 dollars per ounce. The price of silver climbed from $19 an ounce to over $30 an ounce. However, the price of copper has more than doubled due to increased demand for this metal. The price here went from $1.84 to $4.4 per pound. The same results were obtained by Fortescue (2013) in his work that examined the evolution of the price of steel.

RQ2: How has the COVID-19 pandemic affected the development of metal prices?

In this period from 2020 to 2021, during the COVID-19 pandemic, there was growth in all the listed metals. For steel, this was mainly due to the COVID-19 closures in China, which is its largest producer. Prices here went from 3,400 yuan per ton to 5,800 yuan per ton. Copper has grown due to increased demand for electronics and the COVID-19 mentioned above lockdowns in China. Due to these factors, the price rose from $2.50 to $4.50 per pound. The prices of silver and gold rose due to the already mentioned understanding of these metals as a safe harbour for investments, but the increased demand for electronics also supported the growth of their prices. Silver went from $17 per ounce to $23 per ounce, and gold went from $1,580 to $1,828 per ounce. Ahmed, Sarkodie (2021) also reached the same values when they examined the development of stock market prices for steel, copper, gold and silver during the COVID-19 pandemic.

RQ3: How did the Russian invasion of Ukraine affect the price of metals?

From 2022 to 2023, a Russian invasion of Ukraine caused uncertainty in world markets. The price of steel and copper fell during this period. However, this drop was caused by the already mentioned prevailing uncertainty and reduced demand for these metals. Steel prices fell from 4,549 yuan to 4,000 yuan per ton, and copper prices fell from $4.3 per pound to $3.8 per pound of copper. In the case of gold and silver, their prices rose again due to the prevailing uncertainty in the markets. Gold's price rose from $1,798 per ounce to $2,000 per ounce, and silver's price went from $22.45 per ounce to $25.47 per ounce. Gajdzik, Wolniak & Grebski (2022) also achieved the same results when they investigated steel price development in Poland.

Conclusion

The work aimed to identify the development of the prices of steel, copper, silver and gold used in the circular economy. The monitored period was 2009-2023.

The goal was accomplished. The results chapter always described the price development of steel, copper, silver and gold during the period of the economic crisis in 2009-2010, then the period of the COVID-19 pandemic in 2020-2021 was described, and the last monitored period was from 2022-2023 when the Russian invasion of Ukraine was underway. Data from monthly price developments on world stock exchanges were used in each of these periods. The monitored metal's average price and mean were always listed for better clarity. The resulting data then showed that even though there was an increase in uncertainty in the markets in the monitored periods, the price of copper, silver and gold increased, but the price of steel decreased. For copper, this growth was driven by increased demand for the metal. The rise in the price of gold and silver was mainly because gold and silver are considered safe havens for investment. However, there was a decrease in demand for steel, and this caused a drop in its price.

Work limits represent a time limit and, simultaneously, the effect of other influences on prices than those already mentioned. The problem with the time limit is mainly with the Russian invasion of Ukraine. Since there have been no peace negotiations and no end to the conflict, we cannot describe its future effect on the prices of these metals. Other influences on metal prices include the prices of emission allowances in Europe and subsidies to support steel production in China. Even in view of the limits of the work, in the following article, we would like to focus on the influence of the price of emission allowances and subsidies on the development of metal prices.

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Czech employees are suffering from a decline in their real wages – Are they entitled to be paid more?

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Abstract

The article deals with development of the average gross monthly nominal and real wages in individual regions and nationally in the Czech economy during the 2011 – 2022 period, with focus on 2022, the year of galloping inflation in the Czech Republic. It examines differences between average gross monthly real wages in individual regions of the Czech Republic and the national average of gross monthly real wage in 2022 There will be a discussion on how to raise the standard of living of households again, about the possibilities of economic policy and the circumstances and consequences of increasing nominal wages. The article presents development trends of the average gross monthly nominal, real wages, and the price level for the following years 2023 and 2024. In addition, the article reveals to which year in the past the household standard of living fell, according to the development of the average gross monthly real wages, at the national level and in Czech individual regions.

Keywords: inflation, galloping inflation, real wages, nominal wages, standard of living, anti-inflationary policy, real consumption

Introduction

The aim of the article is to examine the development of average gross monthly nominal and real wages in the Czech Republic, with focus on differences among the Czech regions and to point out the development and change in standard of living, expressed in the amount of goods and services that employees and subsequently households could purchase, under conditions of rapid growth in the price level mainly in 2022.

The Czech economy has experienced an increasing trend in the standard of living until 2022. The growth of the standard of living has been accompanied by an increase in wages, both, nominal, and real until 2022. But in 2022 the growth of the price level exceeded the growth of nominal wages and real wages started to fall. The rate of inflation jumps to a double-digit or "galloping inflation" in 2022, the last time it happened in the 1990s in the Czech economy. According to the Czech Statistical Office (2023a), the average year-on-year inflation rate was 15.1% in the Czech economy in 2022. The causes of this increase in the price level lie in the deepening energy crisis supported by the ongoing Russia´s war against Ukraine. The growth in global demand for energy and the decrease in the supply of resources have become the breeding ground for a rapid rise in the price level. Economies have barely recovered from the recent coronavirus crisis and after they must struggle with these crises. Economists talk about negative supply shocks that cause the rise in the price level. Aggregate demand was revived after the pandemic crisis, and since 2021 the Czech real gross domestic product (GDP) has been growing only at a gradual rate. At the same time, the government debt of the Czech economy has been growing, and the Czech government is currently dealing with the adaptation of government expenditures to the rise in the price level, and is trying to reduce the excessive state budget deficit.

This inflationary period is not easy for all economic entities including households. Households notice that prices of goods and services are rising, but their nominal wages have not yet been adjusted for the rising price level. When considering the standard of living as a purchasing power of their wages, households go back inevitably to the past.

Literature Review

When price levels increased significantly in economies, the articles examining causes of inflation and the behaviour of economic entities in an environment of relatively high inflation began to appear. Some economists call this inflation the "quasi-inflation" and Galbraith (2023) revealed that it is difficult to explain the current inflation with use of conventional tools, such as Phillips Curve, Non-accelerating inflation rate of unemployment (NAIRU), potential output, or money-supply growth. Some of them are looking for determinants of inflation to identify economic variables that determine the trajectory of inflation as was pointed out by Kinlaw et al. (2023). Several papers deal with the influence of the rising rate of inflation on the behaviour of economic entities, such as the influence of inflation on the consumption behaviour of households. An emphasis is placed on prioritizing current consumption and purchase of durable goods, but also on the growth of household indebtedness as was examined by Ryngaert (2022), or the estimating the level of food needs saturation and changes in behaviour of households in a country (Szwacka-Mokrzycka, Lemanowicz, 2023). Another important focus is on workers´ perception of how their real wages are falling, and on their need to be paid more. Very important is the anti-inflationary policy that seeks to prevent the emergence of an inflationary spiral. Some papers explore the effect of workers´ efforts on the level of nominal wages in an inflationary environment, seeking optimal inflation rate and "faire" wage as highlighted by Miura (2023). Firms realize that in an inflationary environment they must increase wage rates, but this step will increase their labour costs and it appears that firms are trying to limit other components of worker costs, such as bonuses and benefits or side salaries (Caloia, Parlevliet & Mastrogiacomo, 2023).

Wages and their differences are determined in labour markets with a particular type of competition. One common source of differences in wage rates is represented by human capital. In addition to educational differences due to the different human capital determining the level of wages, there are also geographical (intercity and interregional), discrimination differences (paying more or less because of gender, race, age, religion, or disability), and compensation differences, where compensation differences mean higher pay to compensate for the risk associated with job – e.g., payments to soldiers, policemen, firefighters (Cahuc, Carcillo & Zylberberg, 2014).

Several theories explaining the wage determination deviating from the market equilibrium level can be mentioned here. In the "efficiency wage theory" employees are paid more above the market rate, so they will be motivated to work harder, be more productive and less likely to leave their jobs. It is assumed that the cost reduction due to higher productivity will outweigh the cost increase of paying above average wages, and this will increase the profitability of the firms, which can reduce costs associated with employee fluctuations in industries (Mankiw, Taylor, 2021). The "wage-fund theory" says that wages are dependent on the relative amounts of capital available for the payment of employees and the size of the labour force. Wages can rise only with an increase in capital or a decrease in the number of workers. Although the size of the wage fund could change over time, at a given time it is fixed (Longe, 2009). The "residual-claimant theory of wages", according to Walker (1891), holds that wages represent the remainder of total industrial revenue after rent, interest, and profit (which were independently determined) were deducted. In the "bargaining theory" wages and other working conditions are determined by workers, employers, and unions, who determine these conditions by negotiation. In this theory there is no single economic principle or force governing wages (Davidson, 1898). With application of the "signalling theory", firms are more likely to provide higher wages to job candidates with certificates, degrees, and other credentials that "signal" more excellent knowledge or skill, and due to these qualifications, specific individuals have a higher salary than others (McCormick, 1990).

Methods and Data

According to the availability of statistical data from the Czech Statistical Office in the mid-2023, the investigated period 2011-2022 was chosen, for which complete data from all regions of the Czech economy could be found. The data on average gross monthly nominal wages, median gross monthly nominal wages, registered economic entities, and the

Harmonized Index of Consumer Prices (HICP) were taken from the databases of the Czech Statistical Office. Statistical data for conversion to real values of wages (according to the formula: the nominal wage divided by the price level) were used from the Public Database of the Czech Statistical Office, the section of Wages and labour costs. Average gross monthly real wages were calculated using the HICP, where 2015 was chosen as a base period by the Czech Statistical Office. The article pays attention to the effect of galloping inflation in 2022, to the decline in average gross monthly real wages. It examines the reduction in the purchasing power of average gross monthly nominal wages, at the national level and in all Czech regions, and finds the differences among these regions. If there was a negative supply shock, statistical methods cannot be used for a prediction the development of real wages and standard of living in the following years because disinflation is already expected in 2023 and 2024. This article aims to point out the decline in the standard of living of workers in the form of the development of real wages due to the rising price level. A discussion in the article considering other influences and consequences for companies and the economy is no less important.

Research questions

In the context of the current economic environment of rising prices the authors of this article sought answers to these two research questions (RQ1 and RQ2):

RQ1: *How did the galloping inflation of 2022 affect the level of purchasing power of national average gross monthly nominal wages in the Czech economy?*

RQ2: *What are the differences in the level of average gross monthly real wages in the regions of the Czech economy and how do the real wages differ from the national average in 2022?*

Results

First, we focus on the development of the price level. The inflation rate exceeding the 10 percent threshold per year is defined as a galloping inflation. There are no strictly defined parameters of this type of inflation. Usually, the galloping inflation is recognized as a price increase of 10 to 100% per year, sometimes economists introduce other limits, i.e., 10 to 50%. The rate of inflation is generally calculated using the price indexes. The consumer price index reflects household costs and is suitable for converting nominal wages into real ones. Table 1 shows the increase in the HICP in the Czech economy during 2011 – 2022, and in 2022 a relatively higher increase in HICP can be seen. The base period is 2015, it means that the prices of the base period are fixed to this year.

Tab. 1: The development of the Harmonized Index of Consumer Prices (HICP) in the Czech economy (basic index, 2015=100, Classification of Individual Consumption by Purpose (COICOP) during 2011-2022

Year	2011	2012	2013	2014	***2015***	2016	2017	2018	2019	2020	2021	2022
HICP (%)	94.6	98	99.3	99.8	***100***	100.7	103.1	105.1	107.8	111.4	115.1	132.1

Source: The Czech Statistical Office, authors´ processing

According to the Czech Statistical Office, in 2022 the average year-on-year inflation rate reached 15.1%, the nominal wage growth was 6.5%, but the real wage decreased by 7.5%, that indicates a significant decrease in the purchasing power of nominal wages and a decrease in the household standard of living. More specifically, in the 1st and 4th quarters of 2022, real wages fell by 6.7% and in the 2nd and 3rd quarters real wages fell by 9.8%. (Czech Statistical Office, 2023a, 2023c).

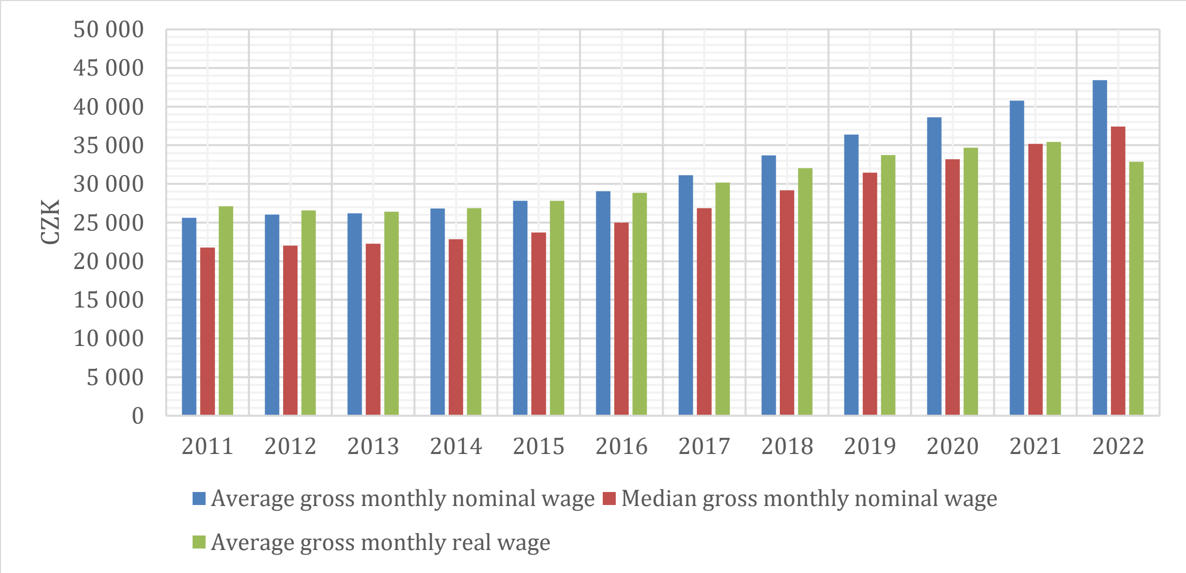
Second, national average monthly nominal wages can be found in statistics, and using the HICP as a price index, the national average gross monthly real wages can be calculated. Table 2 and Graph 1 illustrate the development of national average gross monthly nominal wages, average monthly real wages, and median gross monthly wages in the Czech economy during 2011–2022. After this calculation, a significant differences between national average gross monthly nominal and real wages can be seen, and especially in 2022 (with a reminder of HICP at the level of 132.1% and the average year-on-year inflation rate in the Czech Republic of 15.1%). In 2022, the national average gross monthly real wage was CZK32,863.7, close to the national average gross monthly real wage in 2018 that was CZK32,049.5, exactly 102.5% of 2018, and it means approximately a drop of 4 years back, measured by the criterion of the number of goods and services that households could purchase with their nominal wages, while the national average gross monthly nominal wage was CZK33,684 in 2018, and CZK43,413 in 2022, that is 128.9% of 2018 (The Czech Statistical Office, 2023e).

Tab. 2: The development of national average gross monthly nominal wages, average monthly real wages (using HICP, 2015=100), and median gross monthly wages in the Czech economy during 2011 – 2022 (CZK)

Variable/Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
National average gross monthly nominal wage	25,625	26,033	26,211	26,802	27,811	29,056	31,109	33,684	36,380	38,628	40,777	43,413
National median wage	21,782	21,997	22,266	22,844	23,726	24,982	26,843	29,184	31,449	33,195	35,169	37,418
National average gross monthly real wage	27,087.7	26,564.3	26,395.8	26,855.7	27,811.0	28,854.0	30,173.6	32,049.5	33,747.7	34,675.0	35,427.5	32,863.7

Source: The Czech Statistical Office, authors´ processing

Graph 1: The development of national average gross monthly nominal wages, national average gross real monthly wages (using HICP, 2015=100) and median gross monthly wages in the Czech economy during 2011–2022



Source: The Czech Statistical Office, authors´ processing

In the examined period, the development of national average gross monthly real wage showed an increasing trend (in the last column view) except in 2022. To answer the first research question RQ1, the standard of living of employees (households) decreased on average by 4 years in 2022, due to a significant increase in the price level in this year, while the national average gross monthly nominal wage showed the increasing trend throughout the period.

Third, we focus on the development of average gross monthly nominal and real wages in fourteen regions of the Czech Republic. Table 3 contains gross monthly nominal wages in all Czech regions during 2011 – 2022 and Table 4 includes gross monthly real wages in the regions during 2011 – 2022.

Tab. 3: The development of average gross monthly nominal wages in Czech regions during 2011–2022 (CZK)

Year/ Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
PHA	34,403	35,356	35,155	35,343	36,371	37,387	39,782	42,502	45,888	47,602	50,494	54,015
STC	25,605	25,923	26,302	27,046	27,997	29,170	31,457	34,390	37,151	39,104	40,585	43,536
JHC	23,040	22,871	23,429	24,239	25,246	26,537	28,093	30,620	32,821	35,301	37,715	39,728
PLK	24,086	24,295	24,698	26,004	27,013	28,182	30,700	33,020	35,264	37,613	39,400	41,436
KVK	21,568	21,663	22,333	23,008	24,119	24,893	26,999	29,236	31,710	33,534	35,611	37,512
ULK	23,081	23,608	23,886	24,331	25,301	26,538	28,369	30.802	33,375	36,088	38,027	40,223
LBK	23,240	23,850	24,381	25,114	26,358	27,126	29,121	31,615	34,169	36,127	37,855	39,746
HKK	22,697	23,371	23,639	24,348	25,192	26,578	28,580	31,373	34,357	36,693	38,772	41,187
PAK	22,792	23,080	23,187	23,879	24,856	26,087	28,006	30,358	32,612	34,814	36,642	38,866
VYS	22,680	23,272	23,745	24,347	25,258	26,629	28,568	31,002	33,422	35,694	37,693	39,864
JHM	24,518	25,153	25,587	26,079	27,051	28,319	30,311	32,639	35,439	37,687	40,308	43,071
OLK	22,670	22,754	23,203	24,081	24,584	25,643	27,486	30,073	32,695	35,049	37,075	39,079
ZLK	22,461	22,517	23,117	23,755	24,554	25,953	27,565	30,317	32,759	34,928	36,641	38,869
MSK	23,909	24,340	24,397	24,667	25,475	26,388	27,991	30,364	32,826	35,260	37,265	39,631
Average	25,625	26,033	26,211	26,802	27,811	29,056	31,109	33,684	36,380	38,628	40,777	43,413

Source: The Czech Statistical Office, authors´ processing.

The Prague Region (PHA) generates traditionally the highest level of nominal and real wages, the average gross monthly nominal wage increased gradually from CZK34,403 in 2011 to CZK54,015 in 2022, but the average gross monthly real wage fell in 2022 to the level of 2018, exactly to 101.1% of 2018. The amount of the real monthly wage in the Prague Region reached 124.4% of the average value in 2022. But it should be mentioned that the Prague Region has some of the highest housing costs for households than in other regions, and in the long term it shows the lowest an unemployment rate. Because Prague is a capital city, the Prague Region has a privileged position within the Czech economy, main state administration bodies, most financial institutions, and international corporations are based here. About a quarter of Czech national GDP is generated permanently in this region (The Czech Statistical Office, 2023f). The Central Bohemian Region (STC) ranked second at 100.3% of the real national average wage. The level of real wages in this region returned to 2018 (100.7% of 2018). This region is the largest Czech region in terms of land area and population. The region is an important source of labour for the Prague Region, as it surrounds it and complements Prague´s industry. The South Moravian Region (JHM) took the third place with 99.2% of the national average real monthly wage in 2022. Real wage purchasing power went back 3 years to 2019 in this region (99.2% of 2019). The Plzen Region (PLK) and the Hradec Kralove Region (HKK) have almost the same purchasing power of real wages (95%) as a percentage of the national average wage in 2022 and took the fourth and fifth place. The purchasing power of real wages in Plzen Region returned to 2018 (99.8% of 2018) and in Hradec Kralove Region to 2018 (104.4% of 2018). The Plzen Region shows a higher level of wages, especially in the engineering and food industries, companies with foreign capital participation are located here. The Hradec Kralove Region determines its wages mainly in industry, then in agriculture and subsequently in tourism. (The Czech Statistical Office, 2023d).

Tab. 4: The development of average gross monthly real wages in Czech regions during 2011–2022 (CZK)

Year/ Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
PHA	36,366.81	36,077.55	35,402.82	35,413.83	36,371.00	37,127.11	38,585.84	40,439.58	42,567.72	42,730.70	43,869.68	40,889.48
STC	27,066.60	26,452.04	26,487.41	27,100.20	27,997.00	28,967.23	30,511.15	32,721.22	34,462.89	35,102.33	35,260.64	32,956.85
JHC	24,355.18	23,337.76	23,594.16	24,287.58	25,246.00	26,352.53	27,248.30	29,134.16	30,446.20	31,688.51	32,767.16	30,074.19
PLK	25,460.89	24,790.82	24,872.10	26,056.11	27,013.00	27,986.10	29,776.92	31,417.70	32,712.43	33,763.91	34,231.10	31,367.15
KVK	22,799.15	22,105.10	22,490.43	23,054.11	24,119.00	24,719.96	26,187.20	27,817.32	29,415.58	30,102.33	30,939.18	28,396.67
ULK	24,398.52	24,089.80	24,054.38	24,379.76	25,301.00	26,353.53	27,516.00	29,307.33	30,960.11	32,394.97	33,038.23	30,448.90
LBK	24,566.60	24,336.73	24,552.87	25,164.33	26,358.00	26,937.44	28,245.39	30,080.88	31,696.66	32,429.98	32,888.79	30,087.81
HKK	23,992.60	23,847.96	23,805.64	24,396.79	25,192.00	26,393.25	27,720.66	29,850.62	31,871.06	32,938.06	33,685.49	31,178.65
PAK	24,093.02	23,551.02	23,350.45	23,926.85	24,856.00	25,905.66	27,163.92	28,884.87	30,252.32	31,251.35	31,834.93	29,421.65
VYS	23,974.63	23,746.94	23,912.39	24,395.79	25,258.00	26,443.89	27,709.02	29,497.62	31,003.71	32,041.29	32,748.05	30,177.14
JHM	25,917.55	25,666.33	25,767.37	26,131.26	27,051.00	28,122.14	29,399.61	31,055.19	32,874.77	33,830.34	35,019.98	32,604.84
OLK	23,964.06	23,218.37	23,366.57	24,129.26	24,584.00	25,464.75	26,659.55	28,613.70	30,329.31	31,462.30	32,211.12	29,582.89
ZLK	23,743.13	22,976.53	23,279.96	23,802.61	24,554.00	25,772.59	26,736.18	28,845.86	30,388.68	31,353.68	31,834.06	29,423.92
MSK	25,273.78	24,836.73	24,568.98	24,716.43	25,475.00	26,204.57	27,149.37	28,890.58	30,450.83	31,651.71	32,376.19	30,000.76
Average	27,087.74	26,564.29	26,395.77	26,855.71	27,811.00	28,854.02	30,173.62	32,049.48	33,747.68	34,675.04	35,427.45	32,863.74

Source: The Czech Statistical Office, authors´ processing

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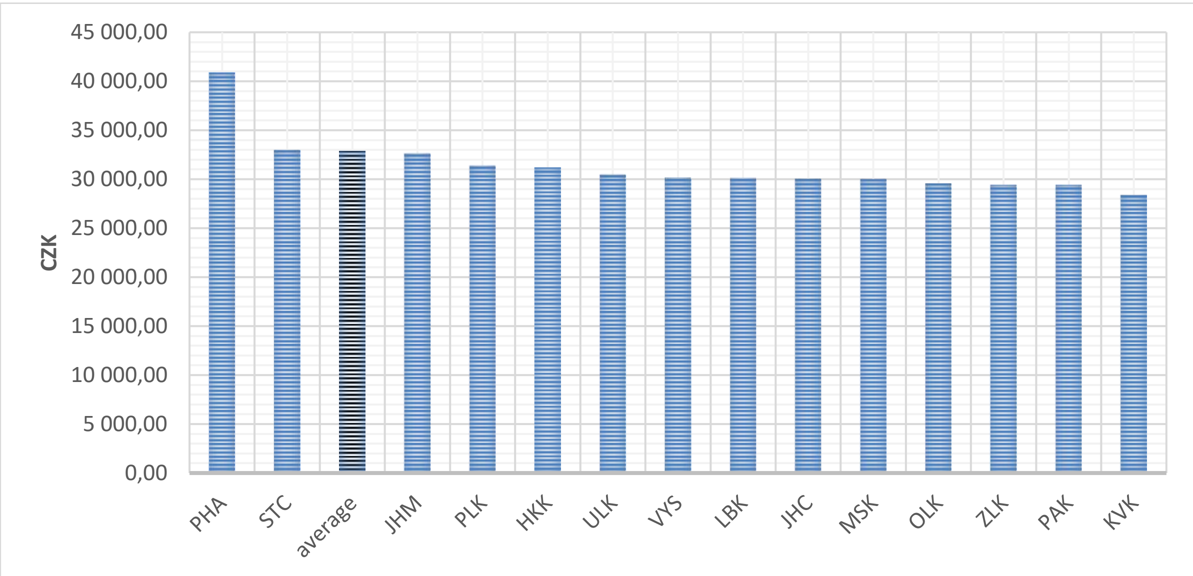
The Usti nad Labem Region (ULK) reached almost the average in purchasing power of real wages in 2022 (93% of the national average monthly gross real wage in 2022) and took the 6th place. This region dropped 3 years back closer to 2019 (98.3% of 2019). The 7th to 10th place was achieved by the Vysocina Region (VYS), the Liberec Region (LBK), the South Bohemian Region (JHC) and the Moravian-Silesian Region (MSK) with the similar slightly below-average values compared to the national average in 2022 (all listed regions reached 91% of the national average in 2022). The Liberec region fell to 2018 (100.02% of 2018), the Vysocina Region to 2018 (102.3% of 2018), the South Bohemian Region fell to 2019 (98.8% of 2019) and the Moravian-Silesian Region dropped to 2019 (98.5% of 2019) compared with the real wage from 2022. The Olomouc Region (OLK), the Zlin Region (ZLK) and the Pardubice Region (PAK) achieved 11th to 13th place with the same value of 90% of the national average in purchasing power of wages in 2022. The Zlin Region and the Pardubice region bounced back about 4 years in real wages due to the double-digit inflation in 2022 (ZLK to 102.0% and PAK to 101.9% of 2018). The Olomouc Region dropped back closer to 2019 (97.5% of 2019). And the last, 14th place belongs to the Karlovy Vary Region (KVK), and it is 86.4 % of the national average wage in 2022. This region with the lowest real wages fell to 2018 (exactly 102.1% of 2018) in purchasing power of wages compared to 2022. Graph 2 shows the listed order of all fourteen regions. The regions are ranked from the highest level of the average gross monthly real wage to the lowest one in 2022.

Graph 2: The ranking of Czech regions according to the level of average gross monthly real wage in 2022



Source: The Czech Statistical Office, authors´ processing

To answer the second research question RQ2, out of a total of 14 regions of the Czech Republic, employees in 9 regions (PHA, STC, PLK, KVK, LBK, HKK, PAK, VYS and ZLK) fell to the level of their standard of living of 2018, it means 4 years back, and in 5 regions

(JHC, ULK, JHM, OLK and MSK) closer to 2019, 3 years back. There is a significant difference between the level of average gross monthly real wage in the Prague Region and other regions in 2022. The last in the graph 2, the Karlovy Vary Region, reached 69.4% of the average gross monthly real wage of the Prague Region, that is 30.6% difference. The Central Bohemian Region and the South Moravian Region recorded the living standards very closed to the national average, and the other regions are below the national average.

Discussion

The previous text documented the decline in the standard of living of Czech households due to the rise in the price level, mainly in 2022. A decrease in the purchasing power of average gross monthly nominal wages is associated with a drop in household consumption. Because household consumption is the most important component of GDP (i.e., approx. 46 % in the Czech Republic in 2022), this reality slows down the growth of the Czech economy. The price growth in 2022 affected mainly necessary goods and services. The decline in household consumption in 2022 was counted and published by the Czech Statistical Office. The household final consumption expenditure fell by 5.5% year-on-year, with the largest decline recorded in purchases of durable goods. Expenditures on food fell significantly, by more than 10% year-on-year, but the decline was also recorded for other items. Only expenses for services grew. (Czech Statistical Office, 2023g).

When the prices of necessary commodities rise, their price demand inelasticity applies. Czech households tried to save as much as they could due to the significant increase in electricity and gas prices. According to the Energy Regulatory Office in the Czech Republic, electricity consumption decreased by 3.9% year-on-year in 2022, and household energy consumption fell by 9%, that is the most significant decline in 20 years, but overall energy sales increased. (Energy Regulatory Office, 2023).

An increase in the average price level is expected to continue in the Czech economy in 2023 and 2024. In addition to market factors, inflationary pressures are created by continuing energy price increases. A double-digit or galloping inflation is expected in 2023, and real wages should continue to decline. According to the Czech Statistical Office, the real wage fell for the seventh consecutive time after the end of the 2nd quarter of 2023. The decline in real wages was most pronounced in the middle of 2022, then it has been moderating. (Czech Statistical Office, 2023h). Due to the decline in the standard of living because of galloping inflation in 2022, it can be expected that the pressure to increase nominal and consequently real wages will get stronger and stronger. It is assumed that firms cannot immediately change the amount of labour forces when real wages rise/fall as was highlighted by Krugman (2022) or Broer, Krusell & Oberg (2023). As assumed, nominal wages are rigid in the short run. Different degrees of nominal wage rigidity and their effect on employment and aggregate demand were examined by Jung (2023). Nowadays it will depend on the response of companies if they are willing to raise nominal wages for their employees.

The results in the article showed a decline in the standard of living of employees on average and in individual regions. To answer the question of whether employees should be paid more at this time, the more precise question is how to ensure an increase in their real wages and, consequently their standard of living. An increase in real wages is possible either by increasing nominal wages or by lowering the price level (or both). Ongoing double-digit headline average year-on-year inflation is estimated by the Czech National Bank (2023) at the level of 10.8% for 2023. When considering the increase in nominal wages, which is the willingness of employers, not their obligation, consequently some firms can raise prices of their products. This will reduce the effectiveness of disinflationary macroeconomic policy and the optimal growth of nominal wages must be found preventing the acceleration of inflation, as highlighted by Kamin, Roberts (2023). The increase in nominal wages will also depend on the bargaining power of workers, who can be represented by unions, so the bargaining theory of wages comes into effect in economic practice. This power can act as another factor in influencing employment. Some data support the role of this force on employment and wage variation as was pointed out by Ellington, Martin & Wang (2023). Some companies are willing to raise nominal wages, but the second side is that they are going to reduce employee benefits. Some firms can increase nominal wages and subsequently real wages if labour productivity increases and the economic situation of firms improves, or additional demand for is generated. If the volume of capital and consequently the productivity of labour increase, firms can elevate nominal wages and the wage-fund theory can be applied in practice. This theory is being tested and one result is a positive two-way association between real wages and labour productivity, supporting the induced technical change and efficiency wages theories (Cruz, 2023). Some firms perceive how their competitors in the labour market react to wage increases and can increase the nominal wages to prevent the turnover of their employees and to motivate them to produce more, and the efficiency theory will be applied in practice.

For the economy, the growth of nominal wage rates will be associated with a reduction in employment. Furthermore, it also depends on the microeconomic policy of the government whether it provides support for the maintenance of employment in terms of nominal wage growth and growth in companies´ labour costs. For example, in Germany companies secured employment in the form of short-time jobs instead of layoffs, with a 24.1% increase in notifications, and the number of vacancies decreased by 10.3% during the energy crises (Hutter, Weber, 2023). Subsequently, these reduced working hours will not be reflected in employment. Another factor is the determination of the minimum wage in an environment of galloping inflation. If the level of minimum wage is higher than the level of equilibrium wage, then a restriction of employment will occur.

When considering the decrease in price level, fighting the double-digit rate of inflation is possible by suppressing aggregate demand (using shock, or gradualist method). The use of macroeconomic policy instruments should be conforming and should have a restrictive effect on aggregate demand. According to Hansen, Toscani & Jing (2023) the monetary policy of countries with double-digit inflation rate will need to remain restrictive to anchor expectations and maintain subdued demand. The central bank can use restrictive policies in the form of an increase in basic interest rates, a policy of strengthening the domestic currency through foreign exchange interventions and trying to reduce the expected rate of inflation. Inflation expectation plays an important role in the policy of reducing inflation. The headline rates of inflation are expected at the level of 2.1% in 2024 and 1.7% in 2025 on the official web site of the Czech National Bank (2023). At least all economists consider all aspects including macroeconomic indicators or macroeconomic policy when forming their inflation expectations as was highlighted by Carvalho et al. (2023). Factors such as income, education, age, gender, knowledge about monetary policy (subjective and objective), or political affiliation affect the size of the inflation expected, as surveyed by Hayo, Méon (2023). The government can help reduce the price level through fiscal and microeconomic policies. When using microeconomic policy, the government intervenes in the functioning of energy markets and can set price ceilings. The government can choose restrictive or expansionary fiscal policy instruments to reduce the price level. As restrictive instruments, the government can use the reduction of government spending or the increase of income tax for the excessive profits of energy companies (a windfall tax). During the energy crisis, governments in some economies imposed this windfall tax on the excess profits of energy companies. But it depends on how this additional tax revenue is treated by a government. Vildauer, Kohler & Aboobaker (2023) emphasize the statement if additional tax revenues are redistributed towards workers, it could be an effective instrument of the anti-inflation policy. The government can choose expansionary fiscal policy instruments in the form of a decrease in indirect tax rates (e.g., VAT rates), or it can support companies most affected by the rise in energy prices with subsidies. What is an obstacle (in the case of the Czech economy), is the government´s policy of reducing the state budget deficit. Governments (including the Czech government) are also facing demands from civil servants to elevate their nominal wages, which has an undesirable pro-inflationary effect.

Conclusion

Economists expect a rising standard of living of the economy´s population in the long term. But this can be interrupted by various crises. Mainly the ongoing energy crisis in 2022 caused a significant increase in the prices of goods and services, as the energy prices will be subsequently reflected in all outputs.

This article was devoted to the issue of the development of nominal and real wages in the Czech Republic with a focus on the year 2022 characterized by factors in the form of a high rate of inflation and only a gradual economic recovery. Two research questions were stated: RQ1: How did the galloping inflation of 2022 affect the level of purchasing power of the national average gross monthly wages in the Czech economy? RQ2: What are the differences in the level of the average gross monthly real wages in individual regions of the Czech economy and how do the real wages differ from the national average in 2022?

The results show that in the examined period 2011–2022 in the Czech economy, a growing trend of the national average gross monthly nominal wage and its median can be observed, but the national average gross monthly real wage dropped significantly in 2022. With this, real consumption, or the purchasing power of wages, and the standard of living of the population fell. Due to the galloping inflation in 2022 the purchasing power of wages in the Czech economy returned to 2018 in average and it means four years back, while the nominal wages and median wage grew up in 2022.

Individual regions of the Czech Republic differ in the purchasing power of their average grow monthly wages. The most different from the national average is the Prague Region, exceeding the national average by 24.4 percentage points in 2022, and then the last Karlovy Vary Region, that recorded a decrease of 13.6 percentage points from the national average. The faster growth of the price level in 2022 caused that employees in 9 regions fell to the level of their standard of living of 2018, that is 4 years back, and employees in 5 regions closer to 2019, 3 years back.

The decline in real wages has considerable consequences for the performance of the Czech economy. Real consumption has fallen, and real GDP growth is slowing down as a result. According to Czech National Bank (2023), real GDP is expected to fall by 0.4% annually in 2023. The year 2023 is likely to be a year of continued double-digit or galloping inflation, and real wages may decline in the following quarters as well. The first three quarters of 2023 shows a continuing decrease in real wages, -6.7% in the 1st quarter of 2023, -3.1% in the 2nd quarter of 2023, and -0.8% in the 3rd quarter of 2023, compared to the corresponding period of the previous year, according to the Czech Statistical Office (2023h, 2023i, 2023b). A creeping inflation rate is expected in 2024, and it can be said that based on the growth of nominal wages and expected disinflation, real wages are expected to rise slowly in the following year 2024 unless another crisis occurs.

For further research, authors recommend examining the factors determining wage differences between Czech regions, household costs in individual regions or comparing the effects of the decline in household standard of living with other countries, for example with neighbouring countries of the Czech Republic. There is also space for addressing various types of wage differences, at the national level or among the regions.

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Mitigating challenges: Handling mis sing values and imbalanced data in bankruptcy prediction using machine learning

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Abstract

The research on financial distress has become essential because the predicted results can serve as an early warning for managers, investors, and banks. Financial ratios calculated in financial reports can serve as indicators to assess the company's condition. One of the approaches used for bankruptcy prediction is employing machine learning methods. Data requirements with balanced classes and the need to process data with complete parameters/features are prerequisites for building an accurate bankruptcy prediction model. In this study, we employed data balancing techniques such as downsampling and filling missing feature values using the average of nearest neighbors in data preprocessing before training the prediction model. From our experiments, we found that by addressing missing values and balancing the data, the F1 score of the prediction model using Random Forest (RF) improved by 30% compared to not addressing missing data and data imbalance. Although our testing used the Polish company dataset, which may have different characteristics from companies in other countries, the proposed strategies can serve as an initial approach for training datasets of other companies using machine learning methods.

Keyword: bankruptcy prediction, financial distress, imbalanced data, machine learning, missing value

Introduction

In a business environment filled with uncertainty and rapid economic changes, predicting company bankruptcies holds excellent relevance. Bankruptcy prediction is a crucial aspect of risk management. The prediction enables companies and stakeholders to identify potential financial risks in advance. The ability to predict bankruptcies allows companies to recognize financial and operational risks that could lead to insolvency. By understanding these risks early on, companies can take proactive measures to manage them effectively. Additionally, investors, creditors, and stakeholders require predictive information to make well-informed investment decisions. Accurate bankruptcy predictions help them identify companies with high potential bankruptcy risks, guiding wise allocation of financial resources.

The company's financial reports provide rich and comprehensive data. They utilized financial statements to build bankruptcy prediction models. There are three approaches to constructing bankruptcy prediction models: using statistical, soft computing, and theoretical approaches. The study conducted by Altman in 1968 represents an early research effort that employed statistical methods to predict corporate bankruptcy. Altman utilized discriminant analysis methods to construct his model. This method measures the differences between two or more groups based on variables that distinguish these groups. In this context, Altman used financial variables, known as financial ratios, to differentiate between companies that are likely to go bankrupt and those that are not.

Although the Altman Z-Score model has proven effective in many cases, there are several limitations to the Z-Score model. Z-Score is a static model that assesses the financial condition at a specific point in time. However, in the dynamic business world, rapid changes can occur, affecting the company's finances. This model does not incorporate market volatility into its calculations. Stock or bond market fluctuations can significantly impact bankruptcy risk assessment. Some companies might have internal information not available to the public, which can affect the accuracy of bankruptcy predictions.

Due to these limitations, researchers have turned to soft computing techniques such as artificial neural networks (Atiya, 2001), fuzzy logic (Rainarli, Aaron, 2015), Support Vector Machine (SVM) (Barboza, Kimura & Altman, 2017; Rainarli, 2019), ensemble methods (Tsai, Hsu & Yen, 2014; Barboza, Kimura & Altman, 2017), and genetic algorithms (Bateni, Asghari, 2020). The advantage of soft computing lies in its ability to handle uncertainty, complexity, and non-linearity in data. It can model complex relationships between various financial and non-financial variables, accounting for market fluctuations and industry dynamics. By employing these techniques, research on bankruptcy prediction can leverage machine learning capabilities to identify complex and non-linear patterns in financial and operational company data. Thus, soft computing techniques offer more flexible and adaptable solutions for the dynamic business environment. The study by Korol (2012) indicates that bankruptcy prediction with a statistical model using the Discriminant Analysis Model resulted in an accuracy of 77.77%, whereas employing soft computing methods such as Neural Network or Fuzzy Logic yielded the same accuracy of 87.03%. This difference represents a 10% improvement when compared to the Discriminant Analysis Model.

While developing predictive models using soft computing approaches can predict bankruptcy, there are challenges in building prediction models, especially with machine learning approaches. Challenges such as missing values, imbalanced data, selecting significant features, and using accurate model evaluation become hurdles in constructing prediction models with machine learning. Therefore, in this study, we evaluate various missing value imputation techniques to observe their impact on prediction model formation, compare the effects of downsampling to address imbalanced data, assess multiple machine learning classification methods in bankruptcy prediction, and employ the F1 score to validate model performance. Understanding the profound need for financial statement-based bankruptcy prediction and addressing challenges related to missing values and imbalanced data using machine learning techniques. The purpose of this research is to construct an accurate bankruptcy prediction model using an imbalanced dataset with missing data. Additionally, this study provides valuable insights for scientific knowledge and business practices relevant to financial risk management. The objectives of this research include analyzing the best methods for handling missing data in bankruptcy prediction cases, examining the impact of dataset balancing on the development of bankruptcy prediction models, and evaluating suitable machine learning classification methods for constructing bankruptcy prediction models.

The structure of this manuscript is as follows, beginning with the problem background on the need for soft computing in building bankruptcy prediction models. We explain the challenges of using machine learning and end up with our proposed solution. Section two discusses the review of related machine learning research and its developments. We outline the framework for bankruptcy prediction in section three, followed by the discussion of results in section four. In conclusion, we summarize the experimental findings and end with a suggestion for further development.

Related work

The research on bankruptcy prediction is valuable as an early warning for managerial, investment, and creditor decision-making. Sun et al. (2014) categorize bankruptcy prediction into two approaches: statistical and artificial intelligence. Various statistical methods used include linear discriminant analysis (LDA) (Altman, 1968; Khan, 2018), multivariate discriminate analysis (MDA) (Lee, Choi, 2013; Mihalovič, 2016), quadratic discriminant analysis (QDA) (Brîndescu-Olariu, Goleţ, 2013), logistic regression (logit) (Mihalovič, 2016; Khan, 2018; Pavlicko, Mazanec, 2022), and factor analysis (FA) (Cultrera, Croquet & Jospin, 2017). The statistical model prediction must fulfill the assumption of independent variables, data distribution following a normal distribution, and equal covariance matrices. If the data fails to meet the requirements, the model generated from statistical approaches becomes biased (Sun et al., 2014). Therefore, developing the bankruptcy model using machine learning approaches became imperative.

Researchers have employed machine learning methods such as Gaussian Process Regression (GPR), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and AdaBoost to construct prediction models. Among these methods, Sabek, Horak (2023) used GPR to predict financial distress. The best model was extracted after optimizing the hyperparameters. Remarkably, this fine-tuned model demonstrated outstanding performance. Sabek (2023) conducted an experiment where two distinct ANNs types were pitted against Logistic Regression (LR) to determine if ANNs consistently outperformed regression. Ultimately, his findings led to the conclusion that not all ANNs are superior to regression when it comes to predicting financial health. A study by Barboza, Kimura & Altman (2017) indicated that Random Forest achieved the best performance. Conversely, Danenas, Garsva (2015) optimized SVM to build bankruptcy prediction models. Two challenges arise concerning the construction of prediction models using machine learning approaches: firstly, the issue of imbalanced data (Cleofas-Sánchez et al., 2016), and secondly, the existence of incomplete parameter values in the dataset.

Building prediction models with machine learning requires a substantial amount of data from each class, i.e., the bankrupt and non-bankrupt classes. Bankrupt cases are significantly fewer than non-bankrupt cases. This condition leads to an imbalanced learning process. Learning from imbalanced data tends to be biased because of the model toward recognizing the dominant class. To address the imbalance condition, techniques such as data addition to the minority class (upsampling) and data reduction (downsampling) or their combination are employed. Researchers must limit these processes, as excessive data addition can lead to model overfitting, and reducing data from the significant class can result in misclassification. Additionally, another challenge in utilizing data for training the machine learning model is the need to have complete financial ratio parameters/features in the dataset.

Based on our literature review, this study focuses on data manipulation to overcome data imbalance and missing values. Our testing aims to evaluate the performance achieved when we balance the data and fill in the missing values before training. We employ Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB) classification methods to determine the optimal approach. There are three main processes for building a bankruptcy prediction model, namely: the data preprocessing stage, the training of the prediction model, and testing the bankruptcy prediction model with unseen data. In this research, we conducted data balancing and data imputation processes as part of the data preprocessing. Our data balancing strategy was employed during the training of the prediction model. After the prediction model was developed, we tested it against new, unseen data and measured its success using precision, recall, and F-measure values.

Proposed Method

To obtain a model capable of predicting bankruptcy, we underwent several processes, as depicted in Figure 1. The initial step involved preprocessing the Polish Company dataset. The dataset consisted of 10,503 companies. The bankrupt companies were analyzed between 2000 and 2012, while the still-operating companies were evaluated from 2007 to 2013. To simplify the process, we combined the evaluations from each year as independent conditions, resulting in a total dataset of 43,405 instances. Each instance provided information on the values of financial ratios, comprising 64 financial ratios

(Tomczak, 2016). The Polish Company dataset is a public dataset. This data has incomplete financial ratio values and an imbalanced distribution of bankrupt and non-bankrupt class propositions. We used The Polish Company dataset to assess the success of the bankruptcy prediction model. Although the company data is from the years 2000-2013, developing a bankruptcy model with this dataset can serve as a baseline if implemented on newer datasets. Additionally, in training prediction models using machine learning methods, the more data involved in model training, the better the model can predict bankruptcy for unseen data.

Table 1 provides an overview of the distribution of data for 64 financial ratios. Each financial ratio contains missing values, resulting in fewer values for each ratio than the total dataset, which amounts to 43,405. The minimum and maximum values for each financial ratio vary significantly. Some ratios, such as X5, X15, X27, X43, X44, X55, X62, have a broad range, while others, like X29, exhibit a narrow range. Therefore, we introduced a data normalization process to ensure consistent data ranges across all financial ratios.

There were three stages in our preprocessing. We began by filling in missing values, removing duplicate data, and performing downsampling. Filling missing data was necessary because out of the 43,405 datasets, only 19,737 instances had complete features. Refrain from discarding incomplete data would result in discarding over 50% of the data. We tested three techniques for filling in missing values. The first technique involved using the median value. For each financial ratio feature, we sorted the values from the smallest to the largest and determined the median value. Then, we used the median to fill in the missing values in the dataset. The second technique utilized the modus value. We used the modus value of each feature to fill in the missing values. The third technique involved using the nearest neighbors' values. Determining values based on nearest neighbors involved selecting the number of neighbors to calculate the missing value and then computing the average value from the nearest neighbors' data. The average value we used to fill in the missing values.

We removed duplicate data to prevent redundant training of instances with similar characteristics. Eliminating duplicate data also helped prevent overfitting during the machine learning model training. Furthermore, the imbalance between bankrupt and non-bankrupt companies posed a challenge during model training. The Polish Company dataset recorded 2,091 bankruptcy cases compared to 41,314 non-bankrupt cases, resulting in a class ratio 1:20. Review findings (Sun et al., 2014) highlighted that balancing data did not always yield optimal performance during testing. However, data balancing was crucial in machine learning to prevent overfitting. Therefore, in our testing, we compared the model's performance using data balancing techniques and without them. We employed downsampling to balance the data.

Table 1: Overview of statistical information from 64 financial ratios of The Polish Company dataset

Financial Ratios	count	mean	std	min	median	max
X1 net profit / total assets	43,397	0.04	2.99	-463.89	0.05	94.28
X2 total liabilities / total assets	43,397	0.59	5.84	-430.87	0.47	480.96
X3 working capital / total assets	43,397	0.11	5.44	-479.96	0.20	28.34
X4 current assets / short-term liabilities	43,271	6.31	295.43	-0.40	1.57	53,433.00
X5 [(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365	43,316	-385.35	61,243.03	-11,903,000.00	-1.03	1,250,100.00
X6 retained earnings / total assets	43,397	-0.06	7.20	-508.41	0.00	543.25
X7 EBIT / total assets	43,397	0.09	5.71	-517.48	0.06	649.23
X8 book value of equity / total liabilities	43,311	12.64	505.89	-141.41	1.07	53,432.00
X9 sales / total assets	43,396	2.65	62.93	-3.50	1.20	9,742.30
X10 equity / total assets	43,397	0.63	14.67	-479.91	0.51	1,099.50
X11 (gross profit + extraordinary items + financial expenses) / total assets	43,361	0.13	5.31	-463.89	0.08	681.54
X12 gross profit / short-term liabilities	43,271	1.13	67.59	-6,331.80	0.17	8,259.40
X13 (gross profit + depreciation) / sales	43,278	0.81	86.94	-1,460.60	0.07	13,315.00
X14 (gross profit + interest) / total assets	43,397	0.09	5.71	-517.48	0.06	649.23
X15 (total liabilities * 365) / (gross profit + depreciation)	43,369	1,991.89	96,431.93	-9,632,400.00	846.26	10,236,000.00
X16 (gross profit + depreciation) / total liabilities	43,310	1.41	68.52	-6,331.80	0.25	8,259.40
X17 total assets / total liabilities	43,311	13.80	507.32	-0.41	2.12	53,433.00
X18 gross profit / total assets	43,397	0.10	5.74	-517.48	0.06	649.23
X19 gross profit / sales	43,277	0.16	48.69	-1,578.70	0.04	9,230.50
X20 (inventory * 365) / sales	43,278	243.02	37,545.17	-29.34	35.15	7,809,200.00
X21 sales (n) / sales (n-1)	37,551	3.88	228.67	-1,325.00	1.05	29,907.00
X22 profit on operating activities / total assets	43,397	0.11	5.16	-431.59	0.06	681.54
X23 net profit / sales	43,278	0.14	48.33	-1,578.70	0.03	9,230.50
X24 gross profit (in 3 years) / total assets	42,483	0.27	7.99	-463.89	0.16	831.66
X25 (equity - share capital) / total assets	43,397	0.39	12.89	-500.93	0.38	1,353.30
X26 (net profit + depreciation) / total liabilities	43,310	1.26	66.22	-6,331.80	0.22	8,262.30
X27 profit on operating activities / financial expenses	40,641	1,107.90	35,012.37	-259,010.00	1.08	4,208,800.00

Financial Ratios	count	mean	std	min	median	max
X28 working capital / fixed assets	42,593	6.00	153.47	-3,829.90	0.47	21,701.00
X29 logarithm of total assets	43,397	4.01	0.83	-0.89	4.01	9.70
X30 (total liabilities - cash) / sales	43,278	7.37	814.49	-6,351.70	0.22	152,860.00
X31 (gross profit + interest) / sales	43,278	0.18	48.75	-1,495.60	0.04	9,244.30
X32 (current liabilities * 365) / cost of products sold	43,037	1,162.62	95,593.56	-9,295.60	78.33	17,364,000.00
X33 operating expenses / short-term liabilities	43,271	8.64	118.99	-19.20	4.63	21,944.00
X34 operating expenses / total liabilities	43,311	5.41	120.98	-1,696.00	1.97	21,944.00
X35 profit on sales / total assets	43,397	0.11	4.78	-431.59	0.06	626.92
X36 total sales / total assets	43,397	2.91	62.98	0.00	1.64	9,742.30
X37 (current assets - inventories) / long-term liabilities	24,421	105.09	3,058.43	-525.52	3.10	398,920.00
X38 constant capital / total assets	43,397	0.72	14.75	-479.91	0.61	1,099.50
X39 profit on sales / sales	43,278	-0.29	39.26	-7,522.00	0.04	2,156.50
X40 (current assets - inventory - receivables) / short-term liabilities	43,271	2.15	56.03	-101.27	0.18	8,007.10
X41 total liabilities / ((profit on operating activities + depreciation)* (12/365))	42,651	7.72	1,398.84	-1,234.40	0.09	288,770.00
X42 profit on operating activities / sales	43,278	-0.14	15.99	-1,395.80	0.04	2,156.80
X43 rotation receivables + inventory turnover in days	43,278	1,074.12	147,218.77	-115,870.00	99.40	30,393,000.00
X44 (receivables * 365) / sales	43,278	831.11	110,050.97	-115,870.00	54.77	22,584,000.00
X45 net profit / inventory	41,258	14.83	2,428.24	-256,230.00	0.28	366,030.00
X46 (current assets - inventory) / short-term liabilities	43,270	5.43	295.36	-101.26	1.03	53,433.00
X47 (inventory * 365) / cost of products sold	43,108	357.84	33,146.34	-96.11	38.13	6,084,200.00
X48 EBITDA (profit on operating activities - depreciation) / total assets	43,396	0.03	5.10	-542.56	0.02	623.85
X49 EBITDA (profit on operating activities - depreciation) / sales	43,278	-0.48	45.15	-9,001.00	0.01	178.89
X50 current assets / total liabilities	43,311	5.84	307.38	-0.05	1.22	53,433.00
X51 short-term liabilities / total assets	43,397	0.48	5.44	-0.19	0.34	480.96
X52 (short-term liabilities * 365) / cost of products sold)	43,104	6.48	639.89	-25.47	0.21	88,433.00
X53 equity / fixed assets	42,593	23.77	1,213.80	-3,828.90	1.21	180,440.00
X54 constant capital / fixed assets	42,593	24.65	1,220.88	-3,828.90	1.38	180,440.00
X55 working capital	43,404	7,672.19	70,053.10	-1,805,200.00	1,088.35	6,123,700.00
X56 (sales - cost of products sold) / sales	43,278	-26.22	5,327.86	-1,108,300.00	0.05	293.15

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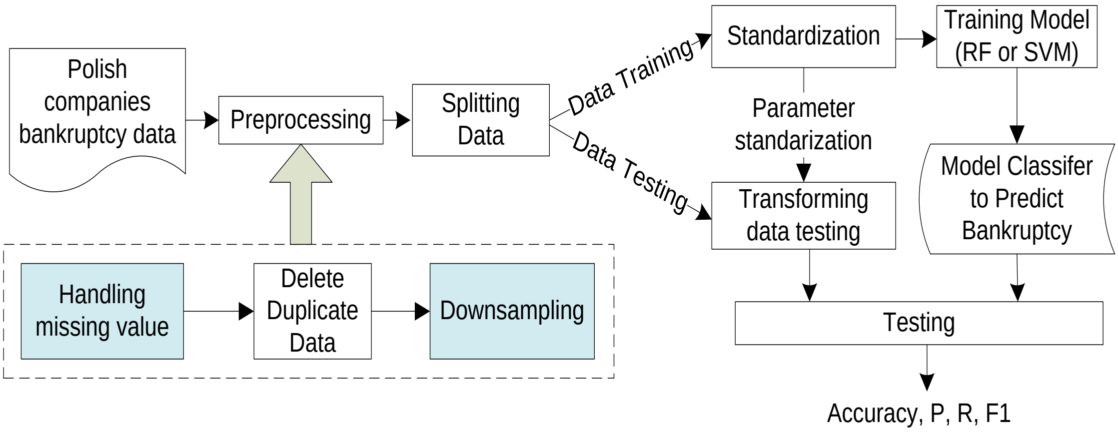
Financial Ratios	count	mean	std	min	median	max
X57 (current assets - inventory - short-term liabilities) / (sales - gross profit - depreciation)	43,398	-0.01	13.67	-1,667.30	0.12	552.64
X58 total costs /total sales	43,321	30.03	5,334.45	-198.69	0.95	1,108,300.00
X59 long-term liabilities / equity	43,398	1.33	122.10	-327.97	0.01	23,853.00
X60 sales / inventory	41,253	448.09	32,345.60	-12.44	9.79	4,818,700.00
X61 sales / receivables	43,303	17.03	553.05	-12.66	6.64	108,000.00
X62 (short-term liabilities *365) / sales	43,278	1,502.33	139,266.70	-2,336,500.00	71.33	25,016,000.00
X63 sales / short-term liabilities	43,271	9.34	124.18	-1.54	5.09	23,454.00
X64 sales / fixed assets	42,593	72.79	2,369.34	-10,677.00	4.28	294,770.00

Source: Tomczak, (2016) and own processing for statistical information

Figure 1. Illustration of bankruptcy detection model addressing missing values and overfitting.



Source: Own model

The stages of predictive model training, as depicted in Figure 1, were as follows:

1) Data preprocessing: This included filling in missing values, removing duplicate data, and balancing training data.
2) Splitting data: We split the data into training and testing sets.
3) Data normalization: This involved transforming the feature values of the training data into standardized values.
4) Training: This process included fitting hyperparameters using Stratified Cross Validation. We used accuracy, precision, recall, and F1 score as model evaluation metrics. The model employed RF and SVM to determine the best classifier model for bankruptcy prediction, specifically for the Polish dataset.

Once we established the model, we tested the test data to assess the model's generalization ability in predicting testing data from the Polish dataset.

There are four possible outcomes when classifying companies into bankrupt and non-bankrupt categories, namely:

1) A company correctly predicted as belonging to the bankrupt class. This event is called True Positive (TP).
2) A company correctly predicted as belonging to the non-bankrupt class. This event is referred to as False Positive (FP).
3) A company that should have been classified into the bankrupt class but was predicted to be into the non-bankrupt class. This is known as False Positive (FP).
4) A company that should have been classified into the non-bankrupt class but was predicted to be into the bankrupt class. This is called False Negative (FN).

According to Dalianis (2018), the precision, recall, and F1 score are calculated using equations (1), (2), and (3), respectively.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

Results

We conducted three tests. The first one was to observe the impact of using three techniques for filling in missing data. The second test compared the effect of changing the data proportions in the downsampling process on the bankruptcy prediction model's performance. The third test involved comparing the model's performance based on the classification methods. We carried out these processes step by step. The optimal conditions identified in each test were used for subsequent testing, resulting in the final model tested being the best predictor for bankruptcy on the Polish dataset.

1. Classification results analysis with the filling techniques for missing data

To analyze the influence of adding data through missing data filling, we conducted three events: filling data using median, mode, and nearest neighbors. We compared the measurement results with data without missing values, meaning we only used complete data and deleted incomplete data. After removing duplicate data, we train the prediction model using the RF algorithm. Balancing data was not applied in this test. The purpose was to observe the impact of using strategy to fill the missing value on the prediction model's performance.

Referring to the accuracy values, Table 2 indicates that the bankruptcy prediction model with only complete data achieves higher accuracy than the model with filled missing data. However, when considering the F1 score, the model with missing values differs from that using missing value filling strategies. The reason is that the non-bankrupt data trained is minor in the model without missing values than the model with missing value-filling strategies. This result aligns with the findings of Zahin, Ahmed & Alam (2018), indicating that missing values in data can affect the efficiency of classification models due to the loss of information from those features. Among the three filling methods, the approach using nearest neighbors (NN) proved the most effective in completing bankruptcy prediction data. The model's performance results were reasonable because the NN strategy filled the data locally. Table 2 demonstrates that the F1 score for the bankrupt class improved by 41%.

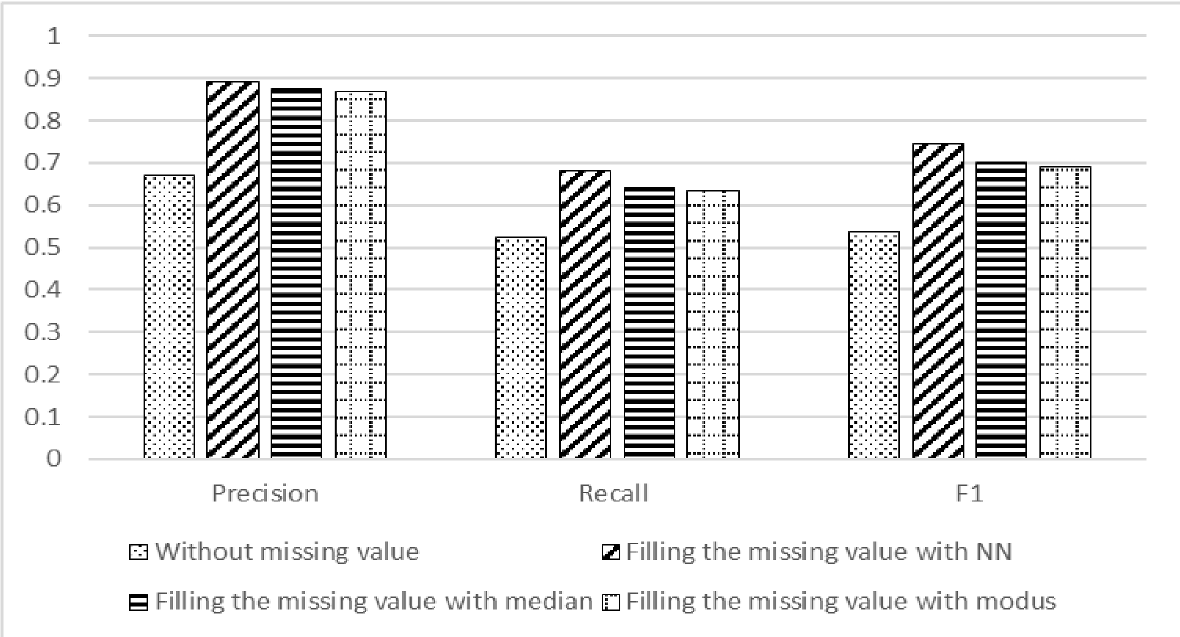
Table 2: Comparison of bankruptcy prediction model performance using RF with missing value strategies

Strategy	Accuracy	F1 score		Average F1
		Bankrupt	Non-bankrupt	
Without missing value	0.9748	0.0859	0.9872	0.5366
Filling the missing values with NN	0.9656	0.5050	0.9821	0.7436
Filling the missing value with median	0.9621	0.4227	0.9804	0.7015
Filling the missing value with modus	0.9611	0.3995	0.9799	0.6897

Source: Own processing

When comparing the precision, recall, and F1 score values from Figure 2, it is evident that filling in missing values enhances precision and recall. The precision, recall, and F1 scores presented in Figure 2 represent the averages of the bankrupt and non-bankrupt classes. The most significant increase in precision occurred for the prediction model utilizing missing data filling with nearest neighbors (NN), with an improvement of 21%. However, the recall values were less substantial than the increase in recall. This phenomenon arises because of the imbalance between bankrupt and non-bankrupt class data. Therefore, in the next experiment, we will evaluate the impact of data balancing on the performance of the bankruptcy prediction model.

Figure 2. Comparison of Precision, Recall, and F1 scores for different filling strategies of missing data



Source: Own processing

2. The impact of downsampling on the performance of the bankruptcy prediction model

Table 3 illustrates the downsampling proportions we employed to balance the data. Given the 2,901 bankrupt data points, we utilized 2,100 data points for the non-bankrupt class. We varied the proportion of non-bankrupt data points. The F1 score for the bankrupt class increased when we reduced the number of non-bankrupt data. We reduced the number of non-bankrupt classes until it was like those of bankrupt classes. Kotsiantis, Kanellopoulos & Pintelas (2006) stated that data imbalance causes classification models to tend to recognize more classes with more significant numbers, in this case, the non-bankrupt class. This result explains why accuracy cannot be used as a reference when fitting a classification model to imbalanced data (Sun et al., 2014).

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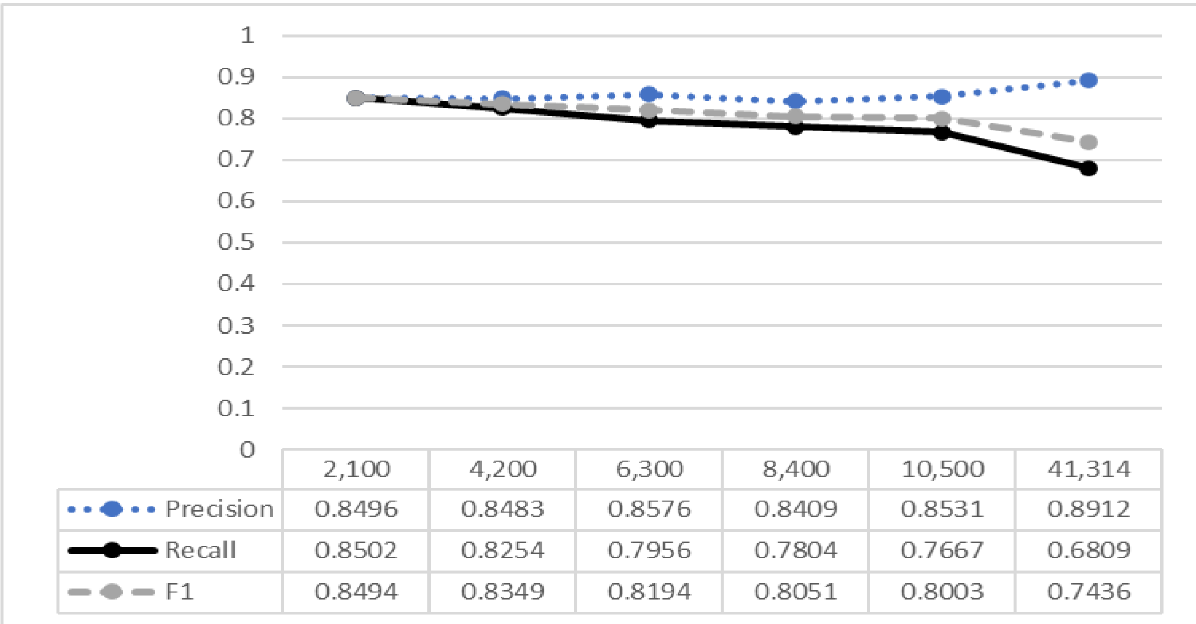
Table 3. Comparison of classification model performance in bankruptcy prediction with down sampling ratios in the RF classification method

Number of data		Accuracy	F1 score		Average F1
Bankrupt	**Non-Bankrupt**		**Bankrupt**	**Non-bankrupt**	
2,091	2,100	0.8494	0.8470	0.8518	0.8494
2,091	4,200	0.8573	0.7741	0.8957	0.8349
2,091	6,300	0.8744	0.7199	0.9190	0.8194
2,091	8,400	0.8878	0.6782	0.9320	0.8051
2,091	10,500	0.9049	0.6559	0.9448	0.8003
2,091	41,314	0.9656	0.5050	0.9821	0.7436

Source: Own processing

Figure 2 shows that by adding non-bankrupt class data, the recall consistently decreases while increasing the precision value. Consequently, when referring to the F1 score, a balanced data condition is the best predictive model, even though its precision could be better than the imbalanced data model. Sun et al. (2014) provides insights on handling imbalanced data. Bankruptcy cases are indeed rare compared to non-bankrupt companies. Therefore, when deciding on using the model, we need to consider the following condition: it is better to predict a bankrupt company as non-bankrupt than vice versa incorrectly. Hence, a high recall value becomes crucial to maintain.

Figure 3. Comparison of precision, recall, and F1 score values with changes in the number of data points in the non-bankrupt class.



Source: Own processing

3. Analysis of classification methods for bankruptcy prediction

We employed three classification methods: Naïve Bayes (NB) as a baseline model, Support Vector Machine (SVM), and Random Forest (RF). In our model fitting process, we utilized the Grid Search method in Python to fine-tune the models based on their hyperparameter values, especially for SVM and RF. For SVM, we tuned parameters such as linear kernel and radial basis function (RBF) kernel, gamma, and C values. In RF, we tuned the number of decision tree estimators and the minimum sample split values to create new trees. Table 4 presents the measurements for these three methods, including comparing their performance without adding missing data.

Among these methods, SVM achieved the highest F1 score in the balanced data group without imputing missing values. SVM performs optimally with smaller, balanced datasets (Danenas and Garsva, 2015). The same trend we observed for the NB method; NB predictive model performance improved when the data was balanced and missing data imputation was not applied. In cases where the data was balanced and handling the missing values, RF emerged as the standout method. The working principle of RF, an ensemble algorithm, explains why RF performs exceptionally well under these conditions (Barboza, Kimura, and Altman, 2017). The study by Barboza, Kimura, and Altman (2017) conducted extensive testing using a large US corporate failure database from 1985 to 2013. They also evaluated predictive models using SVM and found that, for large datasets, RF outperforms SVM. Boosting and bagging algorithms emerged as the most effective choices for bankruptcy prediction.

Table 4. Comparison of classification model performance for RF, SVM, and NB

	Balancing data without missing value				**Missing value and Balancing**			
Classifier	**Accuracy**	**P**	**R**	**F1**	**Accuracy**	**P**	**R**	**F1**
RF	0.7829	0.7835	0.7820	0.7823	0.8494	0.8496	0.8502	0.8494
SVM	0.8217	0.8220	0.8211	0.8213	0.8175	0.8175	0.8180	0.8174
NB	0.6240	0.6783	0.6149	0.5829	0.5219	0.5185	0.5038	0.3892

Source: Own processing.

Table 5 compares precision and recall values for the three classification methods concerning the bankrupt and non-bankrupt classes. SVM with balanced data achieves a balanced recall and precision between the bankrupt and non-bankrupt classes. In contrast, the NB method, despite having a balanced number of bankrupt and non-bankrupt data, fails to detect the non-bankrupt class. This condition is because the NB algorithm requires more non-bankrupt data to recognize the non-bankrupt class. However, adding data with missing values prevents NB from identifying the bankrupt class. We suspect this is due to the non-linear separability of bankrupt data characteristics. Therefore, we cannot use the NB method to build the bankruptcy prediction model. For SVM, the performance tends to decrease when we use data balancing and fill in missing values; however, this decrease is insignificant. The RF method experiences an increase in precision and recall values after balancing data and filling in missing values. The increase in precision and recall occurs for all classes, both bankrupt and non-bankrupt.

Lastly, regarding the limitations of the study, we trained the prediction model using 64 financial ratios as features. If predicting bankruptcy using different financial ratios or introducing additional features beyond the financial ratios, the prediction model needs to be retrained using new training data.

Table 5. Comparison of precision and recall values for bankrupt and non-bankrupt classes in RF, SVM, and NB classification methods.

Classifier	**Precision**		**Recall**	
	Bankrupt	**Non-bankrupt**	**Bankrupt**	**Non-bankrupt**
RF with balancing data	0.7770	0.7899	0.8120	0.7520
RF with balancing data (NN)	0.8262	0.8730	0.8688	0.8315
SVM with balancing data	0.8175	0.8264	0.8421	0.8000
SVM with balancing data (NN)	0.7984	0.8365	0.8289	0.8070
NB with balancing data	0.5874	0.7692	0.9098	0.3200
NB with balancing data (NN)	0.5147	0.5223	0.0581	0.9495

Source: Own processing.

Discussion

We first examined the influence of three different techniques for filling in missing data on the bankruptcy prediction model. These techniques included filling with the median, mode, and nearest neighbors. Our results showed that using complete data without any missing values led to higher accuracy in the bankruptcy prediction model. However, when considering the F1 score, which is a better metric for imbalanced data, filling in missing data with the nearest neighbors approach proved to be the most effective. This was because the nearest neighbors strategy filled the data locally, resulting in a substantial 41% improvement in the F1 score for the bankrupt class. These findings align with previous research indicating that missing data can impact the efficiency of classification models due to the loss of valuable information.

To address the issue of data imbalance, we examined the effect of varying the proportions of non-bankrupt data in the downsampling process. We found that reducing the number of non-bankrupt data points improved the F1 score for the bankrupt class, as imbalanced data tends to favor the majority class. The results highlighted the importance of considering metrics other than accuracy when working with imbalanced data, as accuracy alone can be misleading. In this context, the F1 score became a crucial metric for evaluating the predictive model, with a balanced data condition offering the best overall performance.

We compared the performance of three different classification methods, NB, SVM, and RF. We applied grid search to fine-tune these models based on hyperparameters, with a particular focus on SVM and RF. In the absence of missing data and with balanced data, SVM achieved the highest F1 score. The NB method also showed improved performance when data was balanced and missing data imputation was not applied. However, when the data was balanced and missing values were considered, RF emerged as the standout method. The ensemble nature of RF appeared to contribute to its strong performance under these conditions, which is consistent with previous research findings.

Furthermore, when comparing precision and recall values for the three classification methods, SVM demonstrated balanced recall and precision between the bankrupt and non-bankrupt classes when working with balanced data. NB, on the other hand, struggled to detect the non-bankrupt class, likely due to the requirement for more non-bankrupt data to recognize this class properly. While the performance of SVM decreased slightly when working with balanced data and missing values, the RF method exhibited improvements in both precision and recall values for all classes.

Table 6 presents a comparison of performance values for the predictive model using the Polish Company dataset trained with the RF algorithm for predicting bankruptcy. Two parameters, the Area Under Curve (AUC) and F1 values, are employed to assess the performance of the bankruptcy prediction model. The AUC value illustrates the model's ability to differentiate between two classes, in this case, the bankrupt and non-bankrupt classes. Like the F1 value, the maximum of AUC is 1. The higher the AUC or F1 value, the better the generated predictive model. In the study by Dzik-Walczak and Odziemczyk (2021), the same strategy was employed as ours, using stratified Cross Validation for model training. The proposed predictive model achieved an AUC value 9% higher than that of Dzik-Walczak and Odziemczyk (2021). Different results were obtained when comparing with the study by Quynh and Thi Lan Phuong (2020); the AUC value was higher than the predictive model proposed by us. Quynh and Thi Lan Phuong (2020) used more than one RF classifier to achieve these results. When comparing F1 values, the F1 value of our proposed model is only 0.9% lower than that in the study by Quynh and Thi Lan Phuong (2020).

Table 6. Comparison of Area Under Curve (AUC) and F1 values from other studies for the Polish Company dataset using RF.

Research	**AUC**	F1
Dzik-Walczak and Odziemczyk (2021)	0,8342	-
Proposed Method	0,9269	0,8494
Quynh and Thi Lan Phuong (2020)	0,9931	0,8584

Source: Dzik-Walczak and Odziemczyk (2021), own processing and Quynh and Thi Lan Phuong (2020)

Conclusion

We have conducted tests to build a predictive model using two highlighted strategies in machine learning: balancing data through undersampling and handling missing values. Filling in missing values using nearest neighbors and undersampling techniques enables RF to perform optimally compared to SVM and NB. Although the construction of bankruptcy prediction models heavily depends on the characteristics of the dataset used, the choice of the RF method with data balancing and handling missing values strategies become the initial preference in building predictive models for the dataset. These findings can inform future efforts to enhance the accuracy and reliability of bankruptcy prediction models, which can be of significant value to financial institutions and other stakeholders in making informed decisions.

While it would have been advantageous to include data from a different country to facilitate a comparative analysis between nations, thereby corroborating our findings and enhancing the depth of our discussion, regrettably, the majority of available datasets within the databases are associated with unidentified companies, and the specific countries in which these entities operate remain undisclosed. For future developments, we plan to create a hybrid model by applying optimization methods to select relevant features for bankruptcy prediction.

Declaration of competing interests

The author declares no competing financial interests.

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Distance learning in higher education: reflections of students and academic staff

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Abstract

Distance learning is an educational format that involves guided independent study without the physical presence of academic staff and students in the classroom. Due to the COVID-19 pandemic, distance learning has become the predominant method of education in the Czech Republic. A research study was conducted using a questionnaire survey with the aim of collecting data from academic staff and students of Czech colleges and universities in order to determine their perception of distance learning. 84 responses from academic staff and 161 responses from students were subjected to statistical testing. The results showed that although students' motivation to study in distance learning was higher, compared to motivation during face-to-face learning, and although they evaluated the level of cooperation with classmates positively, they perceived their work and approach to study as average to below average. While academic staff rated their work and approach to teaching, cooperation with colleagues and provided study materials as excellent, distance learning was not beneficial for them in terms of acquiring new skills and their work motivation was not proven to be higher. Overall, academic staff expressed higher satisfaction with distance learning than students. Surprisingly, the majority of respondents did not look forward to face-to-face learning.

Keywords: distance learning, higher education, COVID-19, academic staff, students

Introduction

At the end of 2019, the first cases of a mysterious disease of unknown origin were reported in Wuhan, China. Subsequently, it was discovered that the disease was caused by a coronavirus called SARS-CoV-2 and the disease was named COVID-19 (Trojanek et al., 2020). As a result, the governments of most countries have implemented measures to reduce the risk of infection and act as a preventive measure (Zhang, Liu, 2020). One such measure was the implementation of distance learning in schools, including higher educational institutions. During the first wave of the pandemic in April 2020, schools were closed in most countries around the world, affecting approximately 1.6 billion pupils and students, according to UNESCO statistics (Stringer, Keys, 2021). Although some governments have tried to limit further school closures, as of October 2021, a third of the world's countries had schools that were partially or completely closed, according to the World Bank (Munoz-Najar et al., 2021).

The Czech Republic was no exception. On March 10, 2020, the Ministry of Health issued an emergency measure to prevent the spread of the COVID-19 disease. This measure prohibited the personal presence of pupils and students for the purpose of education and study at Czech primary, secondary, higher vocational and university schools and educational facilities. Czech education thus faced several challenges of so-called distance learning, i.e. education based on independent study, managed by the institution, without personal contact between students and academic staff (Průcha, Walterová & Mareš, 2003). During the COVID-19 pandemic, Czech schools operated in a distance learning mode due to the pandemic for several tens to hundreds of distance days remotely. For universities, specifically for the academic years 2019/2020 and 2020/2021, it was a total of 135 days.

The aim of the presented research was to reveal the perception of distance learning in higher education by academic staff and students in this period and to compare the opinions of the affected target groups. The following research questions were asked:

- RQ1: Whether and how the evaluation of one's own work and cooperation with colleagues (classmates) during distance learning differ?
- RQ2: Whether and how the assessment of the quality and benefit of lectures and exercises by academic staff and students differs?
- RQ3: Which aspects of distance learning were most and least satisfying for the respondents?

Theoretical basis

The term "distance learning" has no agreed definition and varies according to different authors. For example, Černý (2015) defines this term as "a form of education in which students are in indirect contact with academic staff, while this education is largely self-directed and the main responsibility for the process and results of education is borne by the student himself." Průcha, Walterová & Mareš (2003) define distance learning as "a multimedia form of controlled education in which academic staff are separated from the students during the education." In general, it can be said that distance learning is a multimedia form of face-to-face education, where the main principle is self-study, the student is not in in direct contact with an academic staff, he works in his environment and the academic staff fulfills the role of a kind of controller and evaluator.

Until 2020, Czech universities did not have much experience with distance and mixed education. University academic staff and students were thus faced with a number of new tasks in managing the crisis situation in education (Dopita et al., 2023). In their study, Dvořáková, Kulachinskaya (2021) demonstrated that universities were able to respond quickly to the transition to distance learning. For academic staff, the change primarily meant a swift transition and subsequent preparation for work in MS Teams. Due to the shift to online education, differences in students' technical backgrounds and their own home environments for distance learning became apparent. Similar problems arose for female academic workers who had to balance work with childcare, compulsory schooling, and their own schedules at the university.

The concept of working and studying from home during COVID-19 has yielded several benefits for individuals. For instance, academic staff demonstrated their ability to adapt, be flexible, and engage in effective planning (Dietrich et al., 2020; Marek, Chew & Wu, 2021). Students, on the other hand, were able to study from home without the limitations of commuting and could utilize their free time productively (Purwanto, 2020).

Nevertheless, studies have identified certain disadvantages. Distance learning is predominantly conducted at home, resulting in a diminished social connection between academic staff and students (Průcha, Míka, 2000). This lack of interaction can lead to feelings of isolation, loneliness, sleep disturbances, and a depletion of energy, all of which can significantly impact an individual's mental health (Casacchia et al., 2021). Maintaining focus during distance learning is challenging as students find themselves in a home environment that may not foster concentration (Kruszewska, Nazaruk & Szewczyk, 2022). Additionally, the use of computers and screens for educational purposes in distance learning can become tiring after prolonged hours. In an environment detached from educational activities, finding motivation to work becomes more challenging. Studies have linked distance learning to decreases in student mastery orientation, engagement, and enjoyment (Fortus, Lin & Passentin, 2022). Furthermore, issues such as low self-discipline and procrastination have been observed (Pelikan et al., 2021). Pedagogues have often been noted to possess a low level of competence in online distance learning, coupled with a lack of technical support (Simonová, Faltýnková & Kostolanyova, 2021). According to research by the server clovekvtistni.cz, technical complications ranked as the third most serious problem in distance learning (Clovek v tísni, 2022).

Several authors have shown that while distance learning worked as a temporary alternative due to COVID-19, it could not substitute face-to-face education. Therefore, so-called blended learning is proposed as an effective combination of these two forms (Almahasees, Mohsen & Amin, 2021; Hrastinski, 2019; Ashraf et al., 2021).

The research is grounded in the Technology Acceptance Model, which centers around new technologies in terms of user acceptance and models the utilization of the given technology by users. The latest iteration of the model is referred to as Technology

Acceptance Model 3 (Venkatesh, Davis, 2000). The model operates under the assumption that the user's perceived ease of use of the given technology is connected to their individual belief about their own work efficiency. This model enables the examination of students' acceptance of distance learning and the exploration of how students react to this method of education. For instance, it helps identify their reasons for accepting or rejecting distance learning.

Methods

In accordance with the topic and objective of the research, a quantitative paradigm was selected for our study. To accomplish this, a questionnaire survey was considered the most effective method of data collection. The questionnaire itself was designed using a self-constructed technique, and the target population consisted of academic staff and students of Czech universities. In order to ensure the accuracy, clarity, and appropriateness of the questions within the questionnaire, a pilot study was conducted with a selected group of students and academic staff of the University of Defense. The questionnaire was subsequently distributed in printed and electronic form, and the primary data collection was carried out between June to July 2021. Participants were informed about the aim and purpose of the research, as well as the methodology of data analysis, while their anonymity was maintained throughout the process.

The sample size for our study was determined through purposive selection. We approached 400 potential research participants, comprising 200 academic staff and 200 students, and ultimately received 245 responses. Among these participants, 84 were academic staff, and the remaining 161 were students from seven different institutions: the University of Defense, Ambis University, the Technical University in Brno, the Czech Technical University in Prague, Masaryk University, Mendel University, and Charles University.

The research sample consisted of academic staff, comprising 56% men and 44% women. Among the respondents, 6% were under 30 years old, 29% were aged 30-39, 24% were 40-49, 20% were 50-59, 15% were 60-69, and 6% were 70 or older. In terms of education, 30% of respondents held the title of engineer or master's degree, 52% held a doctorate, 12% were associate professors, and 6% were professors. Regarding the length of experience, 42% of respondents had up to 10 years of experience, 29% had up to 20 years, 20% had up to 30 years, and 9% had more than 30 years. The majority of respondents specialized in economics and management subjects, including safety management, risk management, human resource management, financial management, accounting, economics, public administration, business economics, and logistics. The questionnaire's intended questions for academic staff are listed in Table 1.

Tab. 1: Questions of the first battery of closed questions – Academic Staff

Academic staff
1.1 Course of distance learning in general (how lectures and exercises took place)
1.2 Own work and approach to teaching and students
1.3 Students' work and their approach to studying (preparation for teaching, completing tasks, communication)
1.4 Cooperation with colleagues during the preparation and course of distance learning
1.5 Course of distance learning in general (how lectures and exercises took place)

Source: Results for presented own research

The research sample of students consisted of 63% men and 37% women. Among the respondents, 78% were between the ages of 19 and 22, 21% were between 23 and 26, and only two respondents were 30 or older. Except for two students in the combined form of study, all others were full-time students across all years of university studies. The questions for students are subsequently listed in Table 2.

Tab. 2: Questions of the first battery of closed questions – Students

Students
1.1 Course of distance learning in general (how lectures and exercises took place)
1.2 Own work and approach to study
1.3. Academic staff' work and their approach to teaching (understandability of interpretation, willingness, communication)
1.4 Quality and availability of materials provided (presentations, scripts, etc.)Cooperation with classmates when solving team tasks
1.5. Quality and availability of materials provided (presentations, scripts, etc.)

Source: Results for presented own research

The questionnaire contained two batteries of closed-ended questions with predefined answers on a 6-point ordinal Likert scale, as well as three open-ended questions related to the research objective. In the first battery of closed-ended questions, respondents were asked to use a numerical scale ranging from 1 to 5 (where 1 indicated the best and 5 indicated the worst, with an additional option for "I cannot rate") to evaluate various aspects of their distance learning experience based on their personal experience.

In the second battery of closed-ended questions, respondents were asked to use a verbal scale (ranging from 'definitely yes' to 'definitely not,' with options for 'neither yes nor no' and 'not being able to evaluate'). They were required to answer the following questions, which are divided according to their intended use for academic staff (Table 3) and students (Table 4).

Tab. 3: Questions of the second battery of closed questions - Academic staff

Academic Staff
2.1 Did the distance learning lectures suit you more than face-to-face teaching?
2.2 Did the training in the form of distance learning suit you more than in the form of face-to-face education?
2.3 Did you spend more time preparing for distance learning than preparing face-to-face teaching?
2.4 Were you more lenient in assessing students during distance learning compared to assessment during face-to-face education?
2.5 Was your motivation to implement the teaching and all the work associated with it during distance learning higher compared to the motivation during face-to-face teaching?
2.6 Did distance learning help you in your personal development? (E.g. development of new abilities, skills)
2.7 Would it suit you to continue in the distance form of education in the future?
2.8 Were you looking forward to returning to full-time education?

Source: Results for the presented own research

Tab. 4: Questions of the second battery of closed questions - Students

Students
2.1 Did lectures in the form of distance learning suit you more than in the form of face-to-face learning?
2.2 Did the training in the form of distance learning suit you more than in the form of face-to-face learning?
2.3 Did you spend more time studying during distance learning than during face-to-face learning?
2.4 Were the academic staff more lenient when evaluating your work during distance learning compared to the evaluation during face-to-face learning?
2.5 Was your motivation to study during distance learning higher compared to your motivation during face-to-face learning?
2.6 Did distance learning help you in personal development? (E.g. development of new abilities, skills)
2.7 Would it suit you to continue in the distance form of education in the future?
2.8 Were you looking forward to returning to face-to-face learning?

Source: Results for the presented own research

Three open questions, used to supplement information and express respondents' opinions, had the following wording:

- What aspect of distance learning suited you the most?
- Which aspect of distance learning suited you the least?
- Do you consider it important to mention any other facts in connection with the conducted research?

To evaluate the quantitative data, a two-sample t-test was used to compare the mean values of the responses of students and academic staff. This test was supplemented with an F-test to determine the correct variant of the t-test. Next, a Chi-square ($\chi 2$) goodness-of-fit test was used to determine whether the distribution of student responses was statistically different from that of academic staff.

The analysis of answers to open questions according to Strauss, Corbin (1999) was used to evaluate the qualitative data. It is not possible to present all the obtained data to the readers, so it was necessary to reduce them. Reducing and organizing the answers (data) then represents selection and interpretation. The results of this analysis were used to clarify and illustrate the quantitative research.

Results and discussion

Table 5 presents the percentage of responses from academic staff to the first battery of closed questions, evaluating aspects of distance learning on a scale of 1-5, and also provides the results of statistical tests.

Tab.5: Results of the first battery of closed questions - Academic staff

Questions	1	2	3	4	5	test	p-value
1.1	20 %	58 %	20 %	2 %	0 %	t-test	0,102
1.2	39 %	51 %	6 %	1 %	3 %	t-test	0,000***
1.3	9 %	30 %	38 %	22 %	1 %	t-test	0,000***
1.4	56 %	26 %	9 %	5 %	4 %	t-test	0,097*
1.5	55 %	36 %	4 %	1 %	4 %	t-test	0,000***

* Statistically significant difference ($p<0.1$)
** Statistically significant difference ($p<0.05$)
*** Statistically significant difference ($p<0.01$)
Source: Results for the presented own research

Table 6 presents the percentage of responses from students to the first battery of closed question, evaluating aspects of distance learning on the same scale of 1-5, and also provides the results of statistical tests

Tab.6: Results of the first battery of closed questions - Students

Questions	1	2	3	4	5	test	p-value
1.1	19 %	46 %	28 %	6 %	1 %	χ^2-test	0,178
1.2	10 %	29 %	34 %	22 %	5 %	χ^2-test	0,000***
1.3	31 %	38 %	25 %	2 %	4 %	χ^2-test	0,000***
1.4	42 %	29 %	19 %	7 %	3 %	χ^2-test	0,117
1.5	28 %	44 %	21 %	4 %	3 %	χ^2-test	0,000***

* Statistically significant difference ($p<0.1$)
** Statistically significant difference ($p<0.05$)
*** Statistically significant difference ($p<0.01$)
Source: Results for the presented own research

Comparing the results of statistical tests for the responses of academic staff and students allows us to demonstrate differences in individual answers. The evaluation of the data in Tables 5 and 6 was used to address RQ1. From a general perspective, the course of distance learning (question 1.1), encompassing the overall method of conducting lectures and exercises, received mostly positive evaluations from respondents. There is no statistically significant difference in the perception of distance learning between academic staff and students. However, a significant difference is observed in the reflection of academic staff and students on their own work (question 1.2) and the work of their 'counterpart' (question 1.3).

While academic staff generally assess their work and teaching approach positively, students often rate their own work and study approach as average or below average. Conversely, students generally evaluate the work of academic staff and their teaching approach, considering aspects such as clarity of interpretation, willingness, and communication, quite positively. In contrast, academic staff more frequently rate students' work and their approach to studying, including factors like level of preparation for teaching, completion of tasks, and communication, as average. Notably, the results of these two questions, exploring the same factor from different perspectives, are entirely consistent. Thus, it can be concluded that the work of academic staff is generally evaluated more positively than that of students.

Both groups also assessed the level of cooperation with their peers (question 1.4). For academic staff, this involved collaboration with colleagues in preparing distance learning, while for students, it entailed teamwork with classmates on assignments. Both academic staff and students perceived the level of this cooperation positively.

Although both groups generally provided positive evaluations for the quality and accessibility of study materials, such as PowerPoint presentations and scripts (question 1.5), a statistically significant difference is observed in the distribution of answers across the first three levels of the scale. More academic staff leaned towards an excellent rating of the provided materials, while students tended towards an average rating.

Table 7 presents the percentage of answers from academic staff to the second battery of closed-ended questions, assessing answers on a word scale, and displays the results of the performed statistical tests.

Tab. 7: Results of the second battery of closed questions – Academic staff

Questions	Definitely yes	Rather yes	Neither yes nor no	Rather not	Definitely not	test	p-value
2.1	15 %	31 %	21 %	22 %	11 %	t-test	0,005***
2.2	41 %	29 %	12 %	17 %	1 %	t-test	0,011**
2.3	3 %	12 %	12 %	42 %	31%	t-test	0,000***
2.4	17 %	25 %	16 %	39 %	3 %	t-test	0,082*
2.5	9 %	24 %	37 %	21%	9 %	t-test	0,000***
2.6	1 %	11 %	11 %	44 %	33 %	t-test	0,000***
2.7	16 %	24 %	20 %	26 %	14%	t-test	0,645
2.8	0 %	1 %	27 %	35 %	37 %	t-test	0,000***

* Statistically significant difference (p<0.1)
** Statistically significant difference (p<0.05);
*** Statistically significant difference (p<0.01)

Source: Results for presented own research

Table 8 presents the percentage of answers of students to the second battery of closed questions.

Tab. 8: Results of the second battery of closed questions – Students

Questions	Definitely yes	Rather yes	Neither yes nor no	Rather not	Definitely not	test	p-value
2.1	16 %	17 %	12 %	20 %	35 %	χ^2-test	0,005***
2.2	26 %	30 %	13 %	24 %	7 %	χ^2-test	0,098*
2.3	30 %	36 %	18 %	11 %	5 %	χ^2-test	0,000***
2.4	6 %	25 %	23%	40 %	6 %	χ^2-test	0,085*
2.5	54 %	27 %	20 %	13 %	5 %	χ^2-test	0,000***
2.6	12 %	26 %	15 %	32 %	15 %	χ^2-test	0,000***
2.7	20 %	21 %	12 %	24 %	23 %	χ^2-test	0,189
2.8	7 %	22 %	19 %	28 %	24 %	χ^2-test	0,000***

* Statistically significant difference (p<0.1)
** Statistically significant difference (p<0.05);
*** Statistically significant difference (p<0.01)
Source: Results for the presented own research

Comparing the results of statistical tests of academic staff and students' responses demonstrates the differences between the two groups. The evaluation of the data in Tables 7 and 8 was used to address RQ2.

While students expressed greater satisfaction with face-to-face lectures, academic staff, on the contrary, were more satisfied with distance lectures (question 2.1). Training in the form of distance learning, however, suited both researched groups more than training in the form of face-to-face teaching (question 2.2). Nonetheless, a slight difference can be observed between the groups. The proportion of positive and negative answers was 70% to 18% for academic staff and 56% to 31% for students. Therefore, it can be concluded that academic staff were significantly more satisfied with distance learning than students.

Another question (2.3) analyzed the time spent on distance learning. Here, a significant difference in the responses of the two groups is found. While almost three-quarters of academic staff responses do not confirm that they spend more time preparing for distance learning than for full-time studies, 66% of student responses state that they spend more time studying during distance learning than during face-to-face teaching.

Regarding the evaluation of students and their work by academic staff during distance learning (question 2.4), both groups more or less agree and declare that it was not more moderate compared to face-to-face teaching.

However, opinions diverge in the question concerning respondents' own motivation (question 2.5). While the positive and negative responses of academic staff are almost balanced, positive responses significantly predominate among students. Thus, the motivation of students to study during distance learning was significantly higher compared to the motivation during face-to-face education. On the other hand, expressing an unequivocal opinion on the motivation of academic staff to implement distance learning compared to face-to-face teaching is not possible.

Although both groups perceive the aspect of personal development similarly (question 2.6), with the majority of academic staff and students stating that distance learning did not help them in the development of new abilities and skills, a closer examination of the answers reveals a significantly higher percentage of negative responses among academic staff than among students. Distance learning, therefore, benefited students more in this respect.

The responses to the question of whether it would be convenient for the respondents to continue in the distance form of education (question 2.7) were almost equal for both investigated groups. However, in the answers to the question of whether the respondents looked forward to returning to full-time education, both groups mostly took an unequivocal position - rather no and definitely not. Nevertheless, a difference between academic staff and students is noticeable, with a significantly higher percentage of negative answers observed among academic staff.

Table 9 presents the results of the correlation coefficient, indicating the mutual dependence between the answers of academic staff to the closed questions of the questionnaire.

Tab. 9: Correlation matrix - Academic staff

	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5	2.6	2.7
1.2	0,517***											
1.3	0,439***	0,209**										
1.4	0,54***	0,496***	0,19*									
1.5	0,475***	0,601***	0,021	0,527***								
2.1	-0,387***	-0,011	-0,09	-0,134	-0,038							
2.2	-0,366***	-0,062	-0,198**	-0,14	-0,112	0,66***						
2.3	0,281***	0,203**	0,302***	0,267**	0,21**	-0,255**	-0,381***					
2.4	0,156*	0,008	0,193*	0,146	0,115	-0,126	-0,366***	0,659***				
2.5	0,25**	0,189*	0,168*	-0,014	0,056	-0,046	-0,137	-0,008	-0,054			
2.6	-0,203**	-0,066	0,053	-0,002	-0,063	0,385***	0,221**	0,048	0,252**	-0,05		
2.7	-0,186*	0,051	-0,229**	0,003	-0,042	0,235**	0,12	-0,002	-0,027	0,014	0,507***	
2.8	-0,436***	-0,082	-0,216**	-0,221**	-0,082	0,822***	0,623***	-0,369***	-0,263**	-0,098	0,378***	0,222**

Source: Results for the presented own research

The strongest positive correlations are observed between questions 1.2 and 1.5, 2.1 and 2.2, 2.1 and 2.7, and 2.2 and 2.7. In other words, academic staff who rated their own work positively also rated the quality and availability of the materials they provided to students positively. If they expressed satisfaction with distance lectures, they were mostly satisfied with distance exercises, suggesting a preference for continuing distance learning. The strongest negative correlations are found between questions 2.1 and 2.8, 2.2 and 2.8, and 2.7 and 2.8. This indicates that the more satisfied academic staff were with distance lectures and exercises, and the more they would be content with the continuation of distance learning, the less they looked forward to returning to face-to-face education.

Table 10 presents the results of the correlation coefficient, illustrating the mutual dependence between students' answers to the closed questions in the questionnaire.

Tab. 10: Correlation matrix - students

	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5	2.6	2.7
1.2	0,306***											
1.3	0,505***	0,283***										
1.4	0,433***	0,125*	0,332***									
1.5	0,347***	0,159**	0,503***	0,305***								
2.1	-0,271***	-0,148**	-0,099	-0,169**	-0,051							
2.2	-0,199***	-0,158**	-0,054	-0,181**	0,067	0,559***						
2.3	0,189***	0,094	0,063	-0,007	-0,001	-0,367***	-0,263***					
2.4	-0,001	-0,324***	0,16**	0,12*	0,068	0,176**	0,181**	-0,036				
2.5	0,148**	0,076	-0,14**	-0,022	-0,068	-0,237***	-0,118*	-0,045	-0,039			
2.6	-0,19***	-0,261***	0,004	-0,09	0,112*	0,488***	0,464***	-0,354***	0,546***	-0,02		
2.7	-0,204***	-0,278***	-0,042	-0,018	0,001	0,358***	0,31***	-0,225***	0,196***	-0,052	0,432***	
2.8	-0,215***	-0,099	-0,122*	-0,108*	-0,083	0,717***	0,571***	-0,458***	0,122*	-0,142**	0,459***	0,395***

Source: Results for the presented own research

The strongest positive correlations are evident between questions 2.1 and 2.7. This means that the more satisfied the students were with the distance learning lectures, the more satisfied they would be with continuing the distance learning. Similar to academic staff, the strongest negative correlations are evident between questions 2.1 and 2.8 and 2.7 and 2.8. This means that the less satisfied students were with distance learning lectures and the less satisfied they were with continuing distance learning, the more they looked forward to returning to face-to-face education.

The qualitative part of the questionnaire, consisting of answers to three open questions, was utilized to address RQ3. Both academic staff and students frequently mentioned time flexibility and the elimination of the need to commute as the most significant benefits associated with the implementation of distance learning *("elimination of time loss associated with commuting", "I used the time saved to prepare new publications" "saving time, I didn't have to move to lectures", "I didn't have to run between classrooms", etc.)*. Other commonly mentioned aspects that satisfied both research groups included the ability to record lectures *("making lectures available to students", "the ability to start the lecture as a podcast at any time", "the ability to download lectures for better preparation for exams", etc.)* and the peace of mind during classes *("it's easier to understand what someone is saying than in a classroom - less strain on the vocal cords of academic staff", "possibility to really concentrate without disturbing classmates", "better concentration than in a hall full of people", etc.)* .

In some students' responses, satisfaction with the non-contact presentation of assigned tasks was observed *("introverts are satisfied when the whole class can't see them during the presentation", "our lectures were from the comfort of home, so I was less nervous", "less stressful situations during a presentation in front of the class", etc.).* However, negative phenomena resulting from the absence of control of active presence in lectures were also noted *("the possibility to do what I want during the lecture", "sleep during the lecture", "during the lecture I could, for example, exercise, clean, cook", etc.).*

The least satisfactory aspect of distance learning for academic staff was clearly the absence of direct contact with students and the associated complications *("talking into a black screen", "communication barrier and student inactivity", "listeners almost have to be persuaded to speak", "low student response , lack of interest in turning on the cameras", "I missed the immediate reactions of the students - facial expressions, gestures - according to which the academic staff can recognize whether the topic is interesting, boring, etc., and can adapt the teaching operatively", "a low possibility of monitoring the pupils' involvement and their more difficult motivation to maintaining attention", etc.).* Shortcomings of a technical nature were also frequently mentioned *("unreliability of the connection or the possibility of making excuses for it", "dependence on computer technology, the need to connect to the Internet", "system outages, unavailability", "fear that the electric current or the optical cable of the connection will fail" , "I have to be able to deal with everything, even if I'm not an IT specialist"...).*

Among students, the most frequently mentioned obstacles were limited social contact and difficulties in maintaining attention *("insufficient contact with academic staff, fellow students and the school", "more difficult communication with fellow students and academic staff, exercises were not so understandable" "it is difficult to maintain attention when we only look at the screen", "low level of motivation, inability to concentrate, many distractions - social networks, etc.", "I was not forced to concentrate and learn", "no activity control", "insufficient verification of actual knowledge, all just they googled it", etc.).*

At the end of the questionnaire, both investigated groups had the opportunity to mention any other facts related to the research and express their proposals for further possible use of distance learning:

- *"The distance model has the potential to be used, for example, for consultations and oral exams, generally when academic staff only interact with one student."*
- *"Certainly part of the teaching could be done online - for example, an introductory lesson or some presentations of student work in smaller groups."*
- *"In case of student illness, distance learning is a possible alternative."*
- *"In my opinion, combined education is appropriate in a university environment, so a combination of distance and face-to-face education."*
- *"The partial use of distance elements even during face-to-face teaching seems appropriate."*
- *"It is desirable to create hybrid learning materials, usable for both face-to-face and distance learning."*
- *"I would consider a certain combination of face-to-face and distance learning of selected subjects to be ideal for lectures, that is, where possible."*
- *"In the future, it would be advisable to combine distance learning, for example, with lectures and then personal meetings as part of seminars."*
- *"I would introduce distance lectures and face-to-face exercises and seminars, this system suits me."*
- *"I don't see a problem with holding large lectures (with 100 or more people) online, but when it comes to smaller groups, it's more of a negative."*

- *“Distance learning is a nice add-on/bonus that can work for certain non-technical subjects; however, in terms of quality, full-time education significantly exceeds distance learning."*
- *"In my opinion, it is more realistic to conduct lectures online, but the lecturer needs to prepare more for the lecture and use interactive elements to better engage the students in the topic, in my opinion, the quality of the exercises cannot be maintained. , although we used all available interactive elements.”*

Conclusion

In general, the implementation of distance learning, encompassing both lectures and exercises, received predominantly positive evaluations from both academic staff and students. However, there were notable differences in satisfaction levels. Academic staff expressed greater satisfaction with the distance format of lectures compared to face-to-face sessions, while students showed a preference for the face-to-face format of lectures. Interestingly, both groups found the distance format of exercises more favorable than the face-to-face counterpart.

Although students exhibited higher motivation for studying during distance learning and a greater percentage acknowledged the development of new abilities and skills, along with positive evaluations of cooperation with classmates, their overall perception of their work and approach to studying was average to below average. This may be attributed to the increased time commitment required for distance learning and the fact that the evaluation from academic staff remained consistently positive.

Academic staff, rating their work, teaching approach, cooperation with colleagues, and provided study materials as excellent, did not report spending more time preparing lectures during distance learning. However, there was no apparent benefit in terms of acquiring new skills, and work motivation did not show a significant increase.

The respondents' comfort with continuing their studies at a distance remains unclear, but it is noteworthy that most respondents did not express enthusiasm for returning to face-to-face education. Interestingly, academic staff showed slightly less excitement than students.

These sociological investigation findings are valid for the given sample and warrant further verification, particularly through quantitative and qualitative approaches. As universities and colleges increasingly introduce study programs in the form of distance learning, the experiences shared by those with prior distance learning experience can assist program coordinators in optimizing the educational process.

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The question of (un)employment - the impact of the coronavirus pandemic on the business model of SMEs

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Abstract

The authors of this article analysed the impact of the COVID-19 pandemic on the financial situation of employees in small and medium-sized enterprises (SMEs) in the Czech Republic. They conducted a questionnaire survey with 251 respondents in October and November 2021. The structure of the respondents was divided according to the size of the firms, the time of operation in the market, and the focus of business activity, which was presented in detail in the tables. Statistical methods including Quadratic SVM (support vector machine) and Gaussian process regression model were used to evaluate the changes in financial valuation among employees during the pandemic. The analysis results showed that most respondents (SMEs) did not experience a difference in their financial valuation, with the most significant salary retention observed in small-sized enterprises with international operations. The statistical methods of Quadratic SVM and Gaussian process regression model contributed to a better understanding of the financial situation of employees during the pandemic. The Gaussian process confirmed that approximately 80% of the respondents did not experience any change in their salary during the pandemic. One positive finding is some small business owners and businesses that took advantage of compensation programs from the government (e.g., nursing, isolation) with positive financial outcomes for their employees. This shows that appropriately designed subsidy policies can benefit SMEs and help them survive difficult times. Overall, it can be concluded that the COVID-19 pandemic has had an impact on SMEs, some of which have been able to adapt and use state support to maintain employment and financial stability. In supporting SMEs, the government should continue to focus its strategies on maintaining jobs and providing financial support during periods of economic crises such as the pandemic. This research provides valuable insights for the formulation and implementation of effective measures to minimize the negative impacts of crises on SMEs and their employees.

Keywords: SME, economic crises, transformation, unemployment, business strategy.

Introduction

It has been more than two years since the world radically changed and the disease called SARS-CoV-2 hit humanity. This new type of coronavirus caused a global pandemic that affected most countries in the world, including the Czech Republic, in the following weeks and it was only a matter of time before this new situation would affect national preparedness for a pandemic and how these countries would respond (Meramveliotakis, Manioudis, 2021). It is already possible to analyse the different steps that states have taken, and, in the mix, it can be concluded that, at least in the beginning, most states have closed their borders, or rather closed their economies and societies (Rodrigues, Silva & Franco, 2021). In the wake of the following developments throughout Europe and the increase in cases in neighbouring countries, governments began to issue many measures whose priority was primarily to prevent the increasing number of infected people. This has had a significant impact on the business sector. All entrepreneurs, tradesmen, and employees affected by the consequences of the coronavirus epidemic had to react to the restrictions imposed by the state. These changes were reflected in the attitude of employers towards their employees who, on the one hand, dealt with the limitation of contact between employees, but also, in some business sectors, there had to be an inevitable reduction in income, which was compensated by several subsidy programs (Kmencová et al., 2019). Employers have been forced to rethink their approach to the work-from-home, or home-office, format (Kučera, Smolková, 2022). As a result of quarantines and reduced risk to business, companies have had to respond by changing internal regulations and home-office working has often become commonplace (Kraus et al. 2020). Some businesses reduced their employees' wages, postponed pay dates, or stopped paying employees altogether because they were unable to cover wage costs due to the spread of the virus and the shutdown of some production. Other firms introduced unpaid leave, which had a significant negative impact on consumption, especially among low-income groups who were unable to cover their expenses (Lee et al. 2020; Sinčić Ćorić, Špoljarić, 2021). All economic policy measures that were subsequently introduced by individual governments in the interest of public health were intended to reduce the impact on the state's economy, both during the crisis and, above all, to kick-start the state's economy after the crisis. Thus, the role of the state was to create economic rules, to apply such economic instruments and measures to keep the state's economy running, and to prevent the emergence of economic irregularities such as unemployment or stagnation, or reduction of wage levels, including the minimum wage. At the present time, where Europe is facing both the ongoing pandemic and, more recently, the war in Ukraine, which has resulted in a massive influx of Ukrainian refugees, especially to neighbouring countries, it is clear that the role of the state will have an irreplaceable influence on the development of these socio-economic irregularities, and that it is the government that will have to implement such government policies and create such effective measures and use such instruments that will lead to stabilization but also to a transformation to a new sustainable economy (Bowles, Carlin, 2020).

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Literature review

Small and medium-sized enterprises (SMEs) make up most businesses worldwide. They are major contributors to job creation and therefore (Bencsink, Juhász & Mura, 2019) have a significant impact on both national and global economic development (Žárská, Sochuľáková, 2022). They play a significant role in the development of the economy in many countries (Thilagavathi et al. 2021). Therefore, it is desirable to create conditions that enable new firms to enter the economy, thereby activating opportunities for job creation, and promoting research, knowledge dissemination, and innovation (Hrmo, Krištofiaková & Barnová, 2020; Domanižová, Milichovský & Kuba, 2020), which ultimately contributes to economic growth (Ahmad Hasan & Barbhuiya, 2021). The example of the Czech Republic can be used to document the impact of SMEs on GDP formation. From the current figures given by the Ministry of Industry and Trade of the Czech Republic in 2021, it can be deduced that it accounts for almost 36% of GDP, a further 54% of value-added and the last very important factor is that SMEs provide more than 60% of unemployment. Similar results are achieved by other European countries, which is why support for SMEs is of the utmost importance. SMEs have a great advantage over large enterprises in that they can better adapt to market changes (Macrohon, Jeng, 2021). Thus, in a turbulent environment, an environment brought about by the covid pandemic among others, SMEs can perceive, seize and respond to opportunities more intensively and effectively (Park, Kim, 2021). When businesses face economic distress, a well-designed subsidy policy increases the likelihood that businesses that take advantage of government subsidies will be able to survive these situations (Bahadur, Baumann, 2021). The effects of government subsidies and support can play major roles in influencing the development of firm performance, but in many cases, they also affect the very existence of SMEs, especially in a risky period, which the COVID-19 pandemic undoubtedly was. Many studies have aimed to make the public aware of the positive impact of financial subsidy incentives on the firm and its performance (Muldoon, Liu & Mchugh 2021). However, it is important to point out the fact regarding the compensation announced in the European area. Most of the covid compensations are considered public aid instruments from the perspective of European and Czech legislation (Office for the Protection of Competition, 2021). Compensation that is granted from public funds and has the potential to favour certain undertakings or specific sectors of the economy, thereby creating the potential to distort the balance of trade between the Member States, may be classified as public aid. The issue of State aid is defined in Articles 107-109 of the Treaty on the Functioning of the European Union ('TFEU'). However, there are exceptions that may be compatible with the internal market. These exceptions allow Member States to use aid for projects in the event of a serious disturbance in the economy of a Member State, such aid must be notified by the provider to the European Commission. The pandemic caused by the COVID-19 disease fulfilled this condition quite clearly, and the European Commission decided that the situation created by this pandemic fully meets the grounds for the use of this exemption and therefore such public aid is compatible with the internal market (European Commission, 2020). On the basis of this adopted exemption, programs may be announced in the form of Limited amounts of aid, loan guarantees, interest rate subsidies for loans, guarantees, and loans granted through credit institutions or other financial institutions, short-term export credit insurance, research and development support to combat COVID-19, investment support for infrastructure, testing and production expansion, investment aid for the production of products designed to combat COVID-19, tax deferrals or social security contributions, subsidies for wage costs of employees to prevent redundancies during the spread of the coronavirus, recapitalization measures for non-financial enterprises and support for non-covered fixed costs, etc. (Bai, Quayson & Sarkis, 2021).

Authors from non-European countries have reached similar conclusions. An expert article by Kawaguchi, Kodama & Tanaka (2021), examined the causality of the effect of anti-corruption policies applied to small-medium enterprises. The authors concluded that one-time and quick subsidies improved the survival and prospects of small firms, including job retention. A paper by Issenova (2021) examines SMEs in Central Asian countries during the COVID-19 pandemic. Studies for 2020 and 2021 were conducted by international organizations such as the World Bank, the Asian Development Bank, and KPMG (Klynveld Peat Marwick Goerdeler). This analysis led to the conclusion that the recovery potential of SMEs in Central Asian countries is directly dependent on the measures taken by the government, and the main instrument is business support in the form of loan refinancing and administrative support measures. SMEs were exposed to various challenges during the global pandemic and their response affected their chances and resilience to overcome the crisis. However, service-based sectors have been hard hit. In an article by Gregurec, Tomičić Furjan & Tomičić-Pupek (2021), they present how the service sector coped with the disruption caused by the COVID-19 pandemic. This research focused on exploring new technologies, particularly in the context of employee-employer communication, and it appears that SMEs that used digital technologies had a better chance of survival (Sagapova, Dušek & Pártlová, 2022). The operation of small businesses in the industry and the impact of the COVID-19 pandemic were explored in a study that was described in an article by Harel (2021). The study examined the extent to which businesses changed as a result of the global COVID-19 pandemic. However, it found that small businesses whose revenue came from subcontractors and the B2B market were likely to fare better in periods of economic hardship (Konečný, Ruschak & Kostiuk, 2023). The study also found that businesses that are active in international markets were far more successful in adapting to changing demands. As part of this study, research was carried out on the various forms of social support directed at SME employees, which showed that national governments should continue to target businesses with strategies aimed at preserving and restoring jobs and should continue to take this form of assistance into account, either in existing or newly developed strategies and programs (Kollmann, Dobrovič, 2022). Several forms of support for sole traders, firms, and employees have been developed to help firms mitigate negative impacts on business. In the Czech Republic, subsidy systems were provided mainly by the Ministry of Labour and Social Affairs and the Ministry of Industry and Trade. The present article focuses on these facts and examines the impact of the coronavirus crisis on employees and possible changes in

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the financial valuation of employees in various SME sectors with different regional business overlaps. A sub-objective is to evaluate the economic and social support of the state for small and medium-sized enterprises. The evaluation focuses mainly on the use of the benefits and supports provided by different ministries (anti-virus, crisis care, "isolation", care for self-employed workers, payment of uncovered costs and rent) and will use specific examples (case studies) to construct model cases and their financial results in the use of different supports for employees (care, isolation) using the wage comparison method (Horák, Mlsová & Machová, 2021). Possible forms and combinations of state subsidies will be applied to small tradesmen in order to analyse the financial benefits of such support used by employees or entrepreneurs themselves (Horák et al., 2020).

Methods and Data

The questionnaire survey was conducted during October and November 2021. Entrepreneurs were approached to participate in the survey through students of VŠTE and members of the Chamber of Commerce of the Czech Republic. The survey involved a total of 251 respondents - entrepreneurs and companies in the category of micro, small, and medium-sized enterprises (hereinafter referred to as "companies involved in the survey" or just as "companies"). The structure of respondents according to size, length of time on the market, and focus of business activity is shown in the tables below.

Table 1: Number of firms participating in the survey by size (number of firms)

Company size	Period of operation of the company on the market				Total
	0–1 year	2–5 years	6–10 years	11 years and more	
0 – freelancer	1	13	2	19	35
1–10 employees – micro company	6	16	23	29	74
11–50 employees – small company		7	8	35	50
51–250 employees - medium-sized company		3	5	84	92
Total	7	39	38	167	251

Source: Own (2023)

To evaluate the firm's approach to the crisis with a specification to detect changes in the status of employee benefits evaluation in the period before and during the COVID-19 pandemic, the authors will use several statistical methods. Among the classification methods, the method that has proven to be the most appropriate for this type of analysis will be selected. The method chosen was the Quadratic SVM (support vector machine) method, which is represented by the authors Cristianini, Shawe-Taylor (2000). This method is one of the relatively newer methods, it is a kind of alternative to the multilayer artificial neural network method (Vochozka, Horák & Krulický, 2020), which is also able to interpret general nonlinear functions. However, the disadvantage of neural networks is that learning is often very difficult, as there is almost always a risk of getting stuck in a local minimum of the error function. Another risk of using neural weights is the need to find many weights in a multidimensional space. In contrast, the SVM method is a method based on so-called kernel machines, using which linear boundaries can be identified while being able to represent highly complex nonlinear functions (Mitchell, 1997).

$$F1 = x1^2 \tag{1}$$

$$F2 = x2^2 \tag{2}$$

$$F3 = \sqrt{2x1x2} \tag{3}$$

As another method, the Gaussian process regression model will be chosen. Gaussian processes allow us to make predictions about the data. They define a priori distributions over functions or initial knowledge about a parameter is expressed before plausible data is available. When data is observed (observed data D under the parameter condition), the plausibility of the data is verified and the data is converted to an a priori likelihood using Bayes' formula, that is, the resulting function takes into account the observed data D. This approach is described by Bayesian statistics. Gaussian processes are based on a multivariate normal distribution. Based on the continuity or discreteness of the data, Gaussian processes are used for regression. According to Rassmussen, Williams (2006), a Gaussian process is defined by a mean function m(x) and a covariance function k(x, x0), the notation of a Gaussian process is of the form:

$$f(x) \sim GP(m(x),k(x,x0)) \tag{4}$$

The function f(x)represents a random variable at x , or m(x) = 0, (function of the mean values)

We then proceed to the a priori distribution, which can be obtained at arbitrary input points $X*$. The apriori distribution represents the expected output values $f*$ of the inputs $X*$ without data, and is defined according to the notation of the apriori distribution:

$$f* \sim N(0,K(X*,X*)) \tag{5}$$

Where $K(X*, X*)$ is a covariance matrix in which the selected covariance function $k(x*,x*)$ is applied to each element. In our case, a linear non-stationary covariance function was used, which has the following form:

$$k(x,x\ 0\ ) = \sigma\ 2\ f\ x\ T\ x\ 0 \tag{6}$$

Where $\sigma\ 2\ f > 0$ is the total variance.

As the next method in the paper, the data visualization method (Parallel Coordinate) will be used. The Parallel Coordinate (PAC) method, also known as parallel axes (Tricaud et al., 2011) is a very useful method for processing datasets using parallel coordinates.

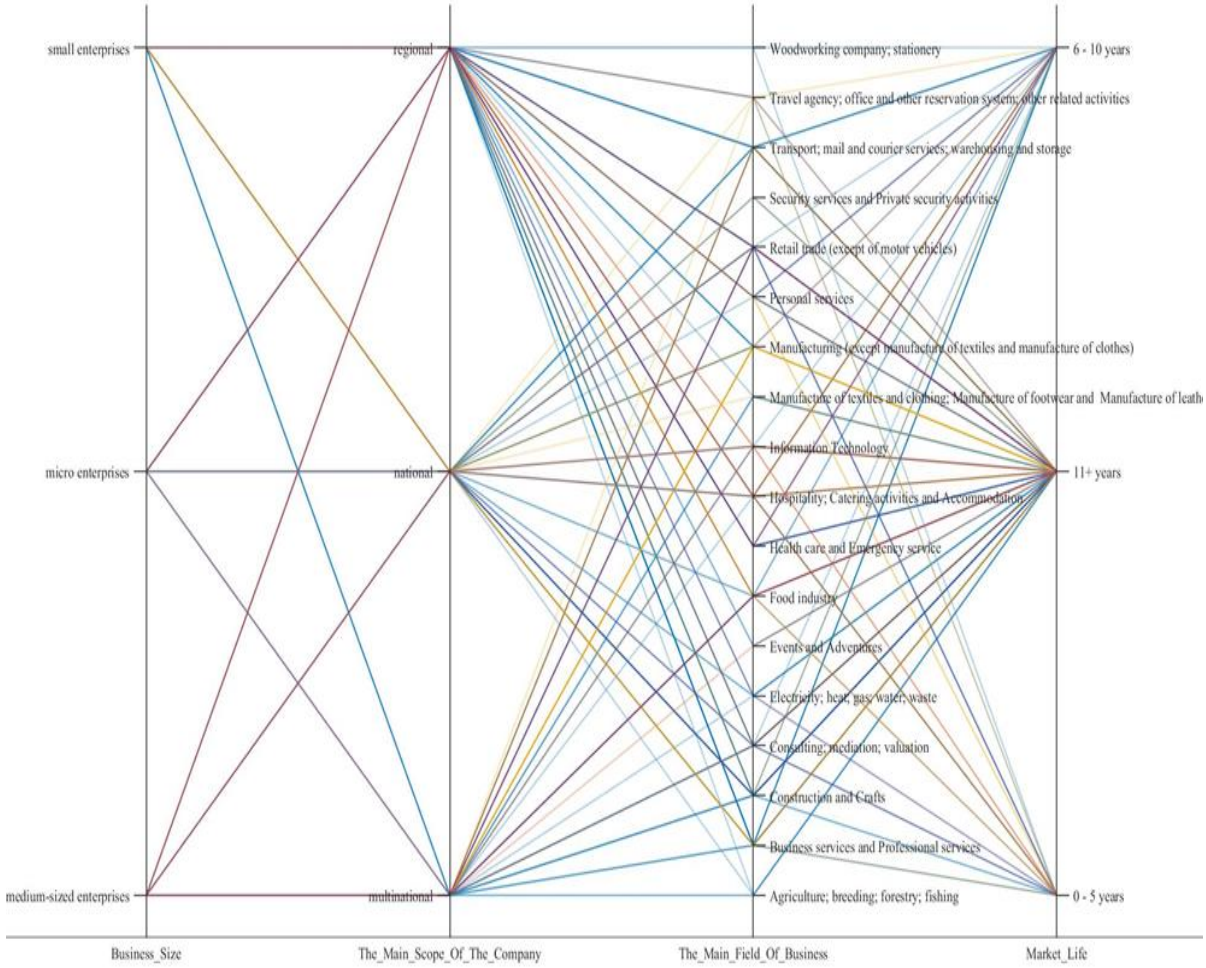
It is used to process such problems where relationships between variables are compared. The advantage of using this method is the ability to see the dataset globally, which means all the data is in one image. The main purpose of looking at the data visually is to see some significant characteristics or anomalies that can be further explored and thus be able to gain further insights into the data. At the end of the paper, a non-experimental method called a case study will be used. The presented case study was conducted based on a survey of wages or average wages in the Czech Republic. Using a specific example, on specific research units (the conversion to the average wage in the Czech Republic will be made), a model example for each type of employee will be constructed using the wage comparison method. The employee who has benefited from the full support of compensation programs (nursing, isolation) compared to an employee working under standard conditions and without the use of compensation programs. A model financial result will be shown using the wage comparison method and including subsequent interpretation. The same will be done for small tradesmen where different forms of compensatory support will be applied. Finally, a summary of the results thus obtained will be made. The chosen case study will serve to interpret the results already obtained from the statistical methods and will also serve to answer the hypothesis posed.

- RQ1: What was the impact of the COVID-19 pandemic on the financial situation of employees in small and medium-sized enterprises (SMEs) in the Czech Republic?
- H1: The majority of respondents (SMEs) did not experience any change in their financial valuation during the COVID-19 pandemic.
- RQ2: What factors influenced changes in the financial valuation of employees during the pandemic in different types and sizes of enterprises?
- H2: Small-sized enterprises with an international presence will experience less change in financial valuation than enterprises operating only nationally.

Results

The basic pillar of the research is to demonstrate the extent of the impact of the covid pandemic on the financial situation of employees working in SMEs. In this regard, we start from a dataset of enterprises, where the basis for answering the set research questions and hypotheses will be based on the structure of the answers of these respondents while understanding the interdependence of the answers between the different areas under study, we will use a schematic representation using the method for data visualization (Parallel Coordinate) that we have mentioned. Within this method, we chose to observe attributes such as firm size, regional scope, sectoral scope, and time in the market with respect to changes in financial valuation.

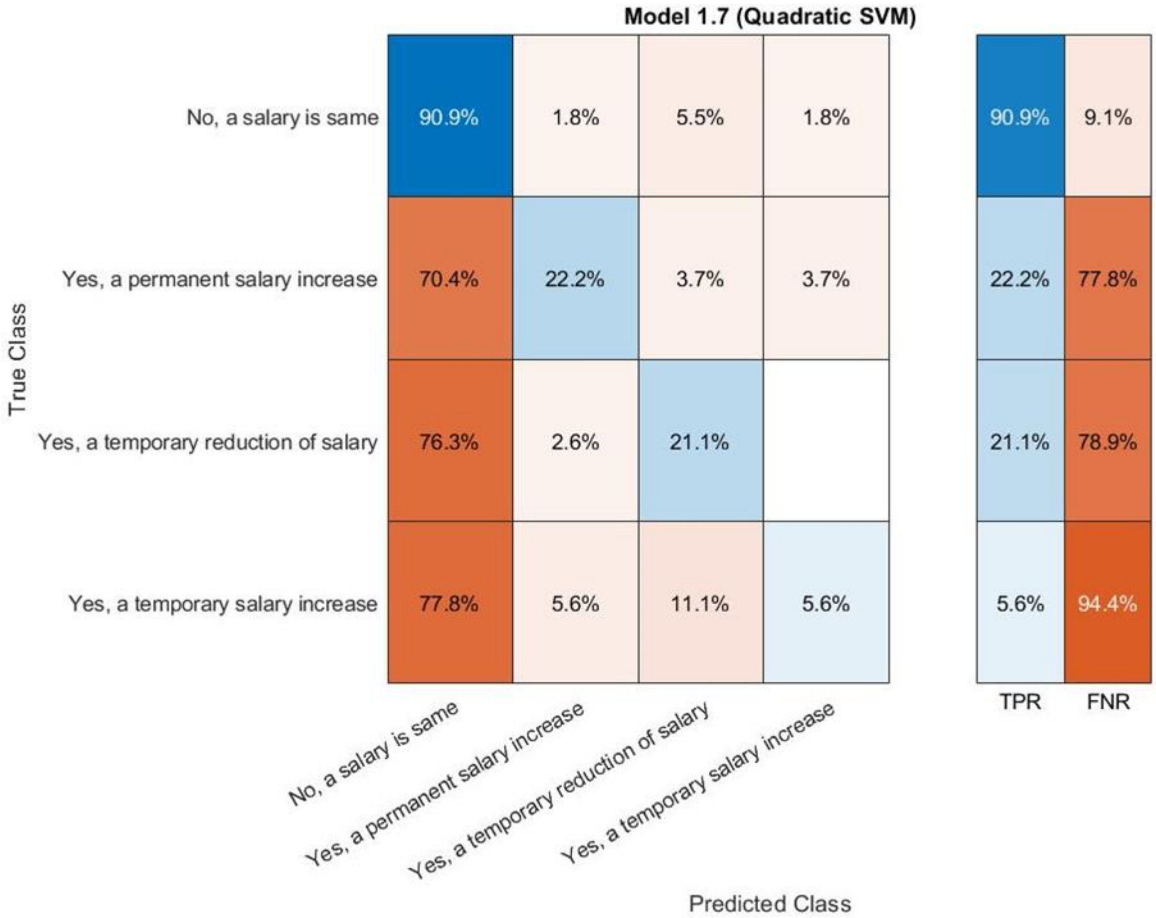
Graph 1: Structure of key research areas (view using Parallel Coordinate)



Source: Own (2023)

It is quite evident that, given the chosen colour scale of the legend, most respondents said that they had not experienced a change in their financial valuation. This is all helped by the fact that the pattern of responses on this issue is balanced across the regional area. In terms of size categorization, the largest contributors to this were small-sized businesses - operating internationally - who had not felt the change in any significant way. On the other hand, enterprises of the same size operating at the national level have already experienced a reduction in the pay of their employees. In the primary sector, we see a trend of no salary increase, i.e. salaries remained the same regardless of territorial scope. A temporary reduction in salary conditions was identified in the tourism sector, where this element was most present in enterprises operating at the national and international levels. Conversely, an increase in salary levels was identified in the health sector, where, even in the light of the pandemic, salary conditions increased dramatically. We also find confirmation that the probability of higher employee pays increases as the years of operation of the enterprise increase. With respect to the pandemic situation, it has been observed that, with few exceptions, the labour market has been significantly affected by this macroeconomic intervention.

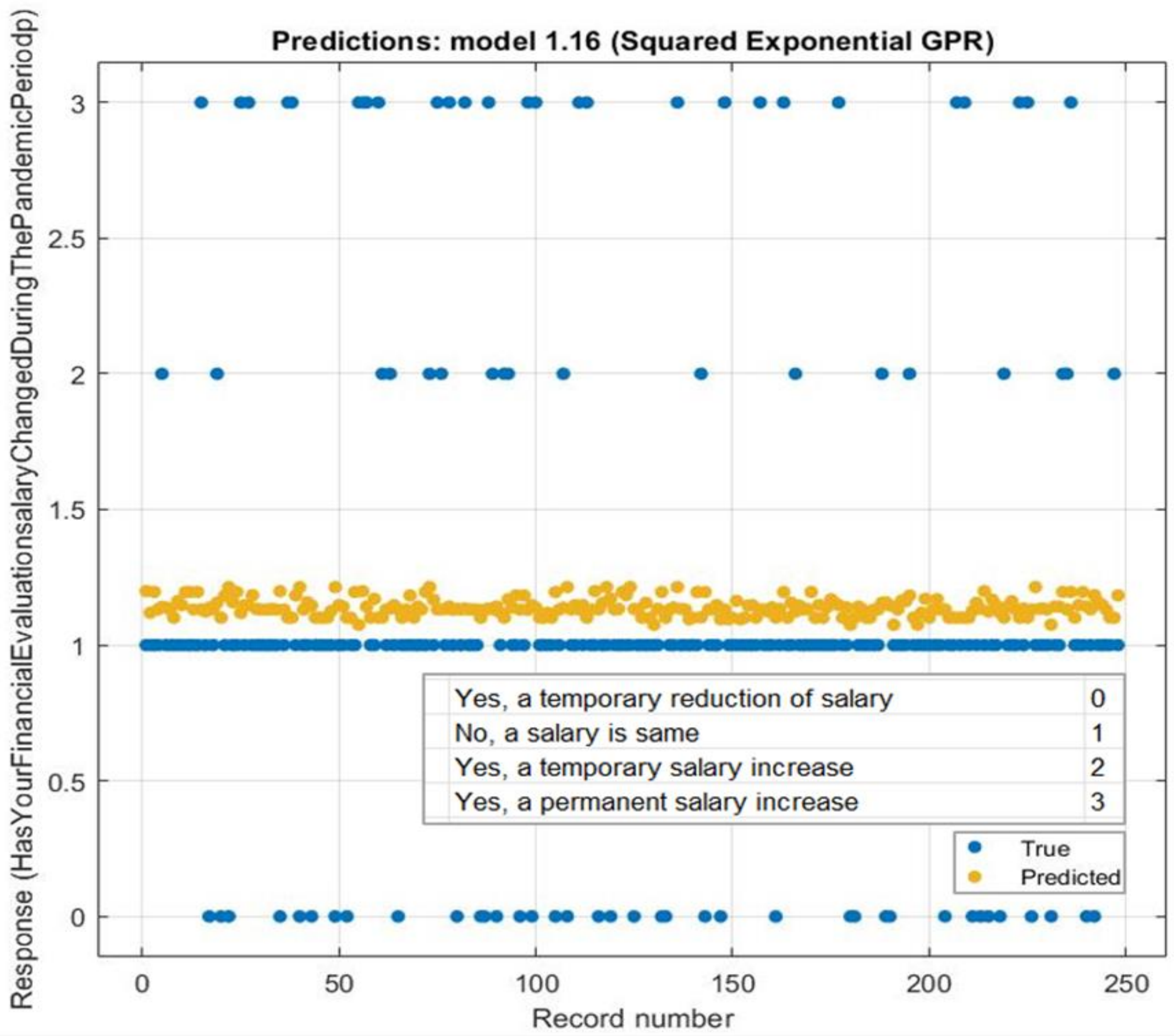
Graph 2: Quadratic SVM: Validation Confusion Matrix: pay change



Source: Own (2023)

After testing the data using Classification Analysis, we found that Quadratic SVM (support vector machine) achieved the best results with a success rate of 65% (see colour matrix). Although this method achieved a relatively low success rate, it proved to be particularly significant for responses marked as "No salary". For this reason, we decided to switch to using a Gaussian process regression model. With this regression model, we achieved success rates more than 80%. This mathematical model allowed us to confirm the high incidence of responses in the "No salary" heading and further predict the data in this field with high accuracy. In this way, we achieved scientific understanding and documented the effective application of regression modelling to our specific data. Our findings suggest that this method could be useful for similar problems and further lead us to better understand and predict relevant outcomes. A graphical result from the GPR is shown below.

Graph 3: GPR - regression model

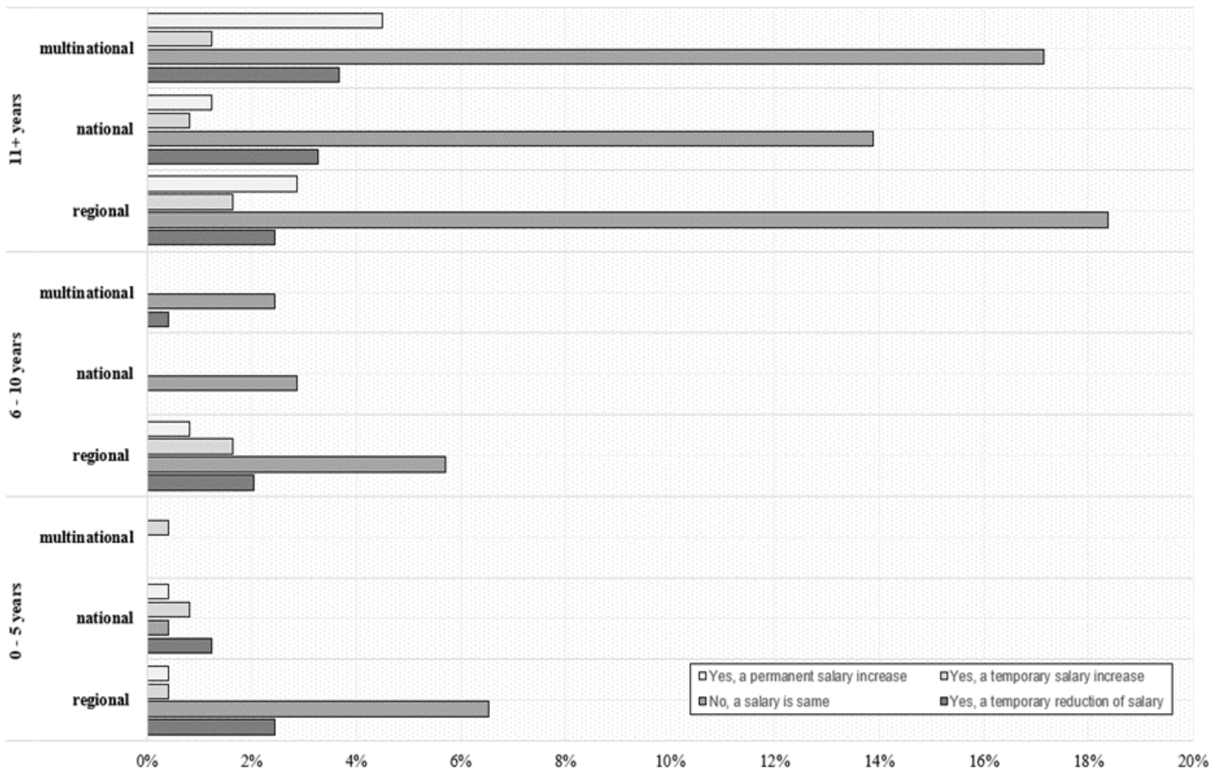


Source: Own (2023)

Here, we have demonstrated the significance of the MSP respondents' responses because their salary ratings did not change during the pandemic. Another result was that there was a gradual decrease in salary ratings, where a significant proportion of respondents are seen, followed by gradual to permanent increases in salaries from a total of 12% of responses. All sectors, such as healthcare, pharmaceuticals, the food industry, and digital technology, have experienced an increase in demand and economic growth, while other sectors, such as tourism, accommodation services, and culture, have been severely affected by restrictions and limitations on mobility. During a pandemic, businesses may have been forced to change their business models or adapt their services and products to new conditions, which could have affected their performance and profitability. Some businesses may have faced financial difficulties and cost-cutting, which could affect their ability to retain existing employees and provide salary increases. For better insight, the following chart shows this trend in the percentage of SME respondents.

The results of the analysis show that during the COVID-19 pandemic, there were significant changes in pay across sectors and depending on the length of time firms had been in the market and the scope of their operations. Within each group of enterprises (0-5 years, 6-10 years, and 11+ years of operation), four scenarios of salary changes were examined: temporary reduction, no change, temporary increase, and permanent increase, the graph can be seen in the following.

Graph 4: Dependence of the evolution of the wage function according to the temporal diversification of firms' functioning in the market and their location by market scope.



Source: Own (2023)

The total of the salary changes in each group of enterprises revealed that enterprises with a tenure of 11 years or more showed the highest overall share of salary changes (71.02%). This suggests that older and more established enterprises were better able to respond to the economic challenges of the pandemic and maintain higher salary levels. Furthermore, different rates of pay changes were observed between regional, national, and international enterprises. Regional enterprises showed more significant changes in pay than national and international enterprises. This may suggest that regional markets were more sensitive to the economic impact of the pandemic and had to respond more quickly to the new conditions. In terms of the different scenarios of salary changes, enterprises with a length of operation of 0-5 years showed the highest percentage of temporary salary reduction (3.67%) and temporary salary increase (1.63%). On the other hand, enterprises with a length of operation of 11 years or more showed the highest percentage of permanent salary increase (8.57%). Overall, the results of this analysis provide valuable insights into changes in pay during the pandemic that can be useful for strategic employment and economic development decisions across industries and enterprise scales. These results can also serve as a starting point for further research and analysis in this area.

Discussion

In the discussion of this article, the authors focus on the analysis of the impact of the COVID-19 pandemic on the financial situation of employees of companies operating in micro, small, and medium-sized enterprises (SMEs) in the Czech Republic. A questionnaire survey was conducted during October and November 2021, with a total of 251 respondents - entrepreneurs and firms - participating. The structure of the respondents according to the size of the firms, the length of time on the market, and the focus of business activity were described in the tables below. Moreover, the analysis methodology, which involved statistical methods such as Quadratic SVM (support vector machine) and the Gaussian process regression model, was presented to assess the change in financial valuation among employees of firms during the pandemic. The research questions and hypotheses explored the loss of employment by industry differentiation (NACE) during the pandemic and the impact of the pandemic on the loss of employment by size categorization of SME firms. The Parallel Coordinate method was used to visualize the data and understand the interconnectedness of the responses between the study areas, clearly displaying the structure of the key research areas. Most respondents did not experience a change in their financial valuation, particularly true for small businesses operating internationally. However, the Quadratic SVM was only about 65% successful and not accurate enough in determining the "No salary" responses. Thus, the Gaussian process with regression model was used, achieving over 80% success and better modeling the respondents' answers on financial compensation. Kollmann, Dobrovič (2022) focus on key factors of organizational and management structures in forming a competitive strategy, greatly influenced by the financial compensation of employees. Our research thus confirms that competitiveness, particularly the growth of salaries, is conditionally dependent on the size and duration of businesses' operations.

Overall, the paper provides a comprehensive view of the situation of firms and employees in the aftermath of the COVID-19 pandemic. The results enhance understanding of the pandemic's impact on the financial valuation of employees in different types and sizes of firms. This finding is corroborated by Gregurec et al. (2021), who emphasized how the pandemic affected not only business models but also the financial health of employees, with most respondents not recording a change in financial valuation. This may reflect the adaptability of SMEs to the changes caused by the pandemic. The statistical methods and data visualizations discussed have contributed to clarifying and interpreting the obtained results. The paper can be considered a valuable contribution to understanding the economic impact of the pandemic on businesses and employees in the Czech Republic. It would be beneficial to discuss the possible limitations of the paper and its contribution to practice and further research. When analyzing the data, some independent variables, such as regional coverage or time on the market, could be examined in more detail to identify specific trends and differences in different areas. Other variables that could affect the financial situation of firms, such as specific government measures or changes in consumer behavior, could also be included. The paper should also discuss these results' implications for practice. Identifying the enterprises most affected by the pandemic could provide valuable information for government institutions and economic support organizations. Designing measures and compensation programs targeting these vulnerable enterprise groups could enable them to better cope with the negative impacts of the pandemic. In terms of further research, it would be interesting to broaden the scope of the analysis and examine the pandemic's impact on the financial situation of employees in other sectors or regions. This could provide a more comprehensive view of the overall impact of the pandemic on the Czech Republic's economy and employment. Moreover, conducting longer-term monitoring and data comparison over several years would help understand long-term trends and possible structural changes in the economy.

Future research on the economic impacts of crises and pandemics could significantly contribute to better understanding how these unpredictable events affect businesses and workers and develop more effective strategies to address and limit their negative impacts. A future research direction could focus on identifying key factors influencing financial compensation, extending research to other variables that could influence employee financial compensation, such as the level of investment in technology and innovation, relationship with suppliers, competitive position in the market, etc. Analyzing these factors can provide a deeper understanding of how firms adapt to crises and how this affects wages and employment, as highlighted by Kawaguchi, Kodama & Tanaka (2021), who closely examine the short- and medium-term effects of anti-contagion and economic policies on small businesses.

Conclusion

The COVID-19 pandemic has had a significant impact on the salaries of employees in micro, small and medium-sized enterprises (SMEs) in the Czech Republic. Based on a questionnaire survey with 251 respondents, an analysis of the impact of the pandemic on the financial situation of these enterprises was carried out. The methodology of the analysis included statistical methods such as Quadratic SVM and Gaussian process regression model and used data visualization using Parallel Coordinate method. The results showed that most respondents (SMEs) did not experience a change in their financial valuation during the pandemic, with the most significant salary retention among small businesses with international operations. However, different sectors showed different responses to the pandemic. Healthcare, pharmaceuticals, the food industry, and digital technologies showed an increase in demand and economic growth, while tourism, accommodation services and culture were severely affected by restrictions and mobility limitations. This suggests that different sectors responded differently to the situation, which is an important lesson for further strategic planning and policy decisions. An important finding was that businesses with a tenure of 11 years or more showed the largest share of salary changes during the pandemic, indicating that older and more established businesses were better able to respond to economic challenges and maintain higher salary levels. There was also a difference in the rate of salary changes between regional, national, and international businesses, with regional businesses showing more significant changes in pay than national and international ones. This suggests that regional markets were more sensitive to the economic impact of the pandemic and had to respond more quickly to the new conditions.

Four scenarios were examined for the analysis of salary changes: temporary reduction, no change, temporary increase, and permanent increase. Enterprises with a length of operation of 0-5 years showed the highest percentage of temporary salary reduction, while enterprises with a length of operation of 11 years or more showed the highest percentage of permanent increase. These findings have the potential to provide deeper insights into salary trends during the pandemic and enable strategic hiring decisions. The research also looked at machine learning methods for predicting "No salary" responses. While the Quadratic SVM achieved a success rate of around 65%, the Gaussian process regression model achieved a success rate of over 80% and was more effective in predicting said responses. This confirmed the effectiveness of regression modelling for specific data and suggested that this method could be useful for similar problems in the future. The findings of the analysis are important scientific knowledge that can serve as a basis for further research and strategic decisions in the field of employment and economic development. Identifying the sectors and enterprises that have been most affected by the pandemic can help government institutions and organizations in designing measures and compensation programs to provide the necessary support to vulnerable groups of enterprises. Extending the analysis to other variables and tracking long-term trends could then contribute to a better understanding of the overall economic impact of the pandemic and help develop more effective strategies for future emergencies.

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