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Impact of COVID-19 on Stock Prices in the Global Video Game Market

Martin Smrt [1,*], Anna Hodinova [2], Robert Kuchar [3]

[1] Institute of Technology and Business in Czech Budweis, School of Expertness and Valuation, Finance + Accounting Group, Czech Budweis, 370 01, Czech Republic
ORCID: 0009-0002-2654-3591
e-mail: 27629@mail.vstecb.cz

[2] Institute of Technology and Business in Czech Budweis, School of Expertness and Valuation, Finance + Accounting Group, Czech Budweis, 370 01, Czech Republic
ORCID: 0009-0001-1983-1619
e-mail: 26674@mail.vstecb.cz

[3] Institute of Technology and Business in Czech Budweis, School of Expertness and Valuation, Finance + Accounting Group, Czech Budweis, 370 01, Czech Republic
ORCID: 8
e-mail: kuchar@mail.vstecb.cz

[*] Corresponding author: Martin Smrt, 27629@mail.vstecb.cz

Abstract

The COVID-19 pandemic has profoundly impacted various sectors, including the global video game market. This study investigates how the pandemic influenced the stock prices of leading video game companies, such as Electronic Arts, Ubisoft, Square Enix, Nintendo, Sony, and Activision Blizzard. The purpose of this research is to understand the relationship between the surge in COVID-19 cases and the stock performance within this industry, providing insights into the sector's resilience and adaptability during unprecedented times. Using a Vector Autoregression (VAR) model, we analysed weekly stock prices and the number of new COVID-19 cases from January 2020 to August 2023. Our methodology included determining the optimal number of lags for the VAR model, verifying data stationarity through the Augmented Dickey-Fuller test, and interpreting impulse response functions to gauge the impact of new COVID-19 cases on stock prices. The main findings reveal that Western companies, such as Activision Blizzard and Electronic Arts, showed more positive responses to changes in COVID-19 case numbers compared to their Eastern counterparts, like Sony and Square Enix. These results underscore the differing impacts based on geographical and market presence factors. Theoretically, this research contributes to the understanding of market dynamics and investor behaviour in the face of global crises. Practically, the findings highlight the video game industry's potential as a resilient sector during economic downturns, offering valuable insights for investors and policymakers.

Key words

video game industry, stock market analysis, crisis response, VAR model, economic resilience, investor behaviour, pandemic impact.

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Introduction

The realm of video games stands as a prominent force within the expansive domain of entertainment and media, showcasing itself as one of the most rapidly expanding industries on a global scale. From its humble beginnings, the industry has swiftly traversed through various evolutionary stages, progressing from traditional arcade machines to cutting-edge virtual reality platforms. Building upon the insights of Belyaeva et al. (2022), who delved into the intricate determinants shaping the landscape of the video game industry amidst socio-economic and technological progressions in the global arena, it becomes evident that several pivotal factors play significant roles in its growth trajectory. Economic indicators such as esports revenue and the size of the economically active populace are crucial drivers, while technological advancements, including the import of ICT services, employment within knowledge-intensive sectors, robust server infrastructure, and innovative business models, serve as pillars supporting industry expansion. The multifaceted actors within the video game market, ranging from hardware manufacturers, developers, and publishers to distributors, retailers, consumers, governmental entities, and video game associations, collectively contribute to the dynamic ecosystem that propels the industry forward (González-Piñero, 2017). The landscape of this industry is prominently shaped by three leading console manufacturers: Sony, Microsoft, and Nintendo. Alongside these giants, video game developers like Activision Blizzard play a pivotal role in driving innovation and content creation. Notably, some console manufacturers, such as Microsoft, Sony, and Nintendo, have expanded their influence by not only manufacturing consoles but also developing and distributing their own video games either through subsidiary companies or subcontractors. Collaboration between video game developers and producers stands as a cornerstone in game creation, with developers contributing their expertise to bring ideas to fruition. Following development, games are distributed through various channels facilitated by distributors, ensuring their availability across multiple platforms. This interconnected ecosystem underscores the reliance of video game developers and distributors on console compatibility, while producers hinge their success on the widespread availability of games (Piñeiro-Chousa et al., 2023). The video game industry has been recognized in literature as a fertile environment for studying the dynamics of innovation related to the introduction of disruptive technologies and subsequent changes in market leadership. The first milestone was the replacement of initial arcade games installed in establishments with console games that allowed for home play, leading to an increase in game diversity. Since then, several generations can be distinguished, marked by significant technological changes and competitive scenarios (Lantano et al., 2022).

The COVID-19 pandemic has presented unprecedented challenges across various sectors, reshaping economies and altering consumer behaviours globally. One industry that has shown remarkable resilience and adaptability during this period is the video game sector. As lockdowns and social distancing measures were implemented, the demand for digital entertainment surged, making the video game industry a focal point of interest for both researchers and policymakers. This study investigates the impact of the COVID-19 pandemic on the stock prices of major video game companies, providing insights into the sector's robustness and its role in economic resilience.

The aim of this paper is to analyse how the COVID-19 pandemic influenced the stock prices of leading video game companies, including Electronic Arts, Ubisoft, Square Enix, Nintendo, Sony, and Activision Blizzard. By employing a Vector Autoregression (VAR) model, this research seeks to elucidate the dynamic relationship between the weekly number of new COVID-19 cases and the corresponding stock prices of these companies.

This study's originality and contribution to the theoretical framework lie in its comprehensive approach to understanding market dynamics during a global health crisis. By focusing on a sector that blends technology and entertainment, this research bridges gaps in contemporary literature, offering new perspectives on how digital industries can serve as economic buffers. Practically, the findings provide valuable insights for investors, policymakers, and industry stakeholders on the resilience and potential growth trajectories of the video game sector in times of crisis.

The structure of the paper is as follows: the next section provides a detailed literature review, highlighting relevant studies and identifying the research gap this study aims to fill. The methodology section outlines the data collection process, the VAR model's application, and the analytical techniques used. The results section presents the findings of the study, followed by a discussion that interprets these results in the context of existing literature and practical implications. The paper concludes with a summary of key insights, limitations of the study, and suggestions for future research.

1. Literature review

In recent years, several studies have emerged that have analysed the impact of COVID-19 on the economy, business, and even human behaviour (King et al., 2020; Kim, 2021; Galindo-Martín et al., 2021; Liu et al., 2020). The pandemic has influenced people's lives worldwide in many ways, including how they spend their leisure time and cope with unprecedented circumstances. The implemented restrictive measures had a profound effect on the social situation, and the overall economy suffered a significant slowdown. However, certain sectors remained unaffected; for instance, the entertainment and video game industry diversified during COVID-19, experiencing an increase in growth rate due to a rise in the number of players and the entry of new companies into the market (Szopik-Depczyńska et al., 2020). Testimonies suggest that many individuals turned to playing video games during the pandemic (Barr & Copeland-Stewart, 2022). Empirical studies and technical analyses have effectively documented shifts in gaming behaviours amid the global pandemic, showcasing a notable surge in player engagement metrics. Research conducted by Şener et al. (2021) underscores a marked rise in the player base, accompanied by increased durations of gameplay sessions and heightened viewership on streaming platforms. In 2020, the number of video game players worldwide dramatically surged to 2.6 billion, and video game sales reached record-breaking figures. It is interesting that many individuals reported extending the time spent playing video games during the early stages of the COVID-19 crisis, believing that gaming helped them cope with such demanding life experiences, reduced their anxiety levels, and alleviated loneliness (Pallavicini et al., 2022). Particularly in the initial phase of the COVID-19 pandemic, video game industry revenues surpassed those of the film industry, and the number of consumers playing video games experienced a dramatic increase (Kim, 2021). This was due to the fact that consumers worldwide were encouraged or even compelled to work from home to protect themselves from the COVID-19 virus and prevent its spread (Bick et al., 2023). During periods of enforced confinement, individuals found themselves confined to their homes, save for essential outings such as grocery shopping, while those infected with the virus and their close contacts were mandated to observe strict isolation protocols (Iorio et al., 2020). Amidst these circumstances, the emergence of digital technologies emerged as a beacon of solace, facilitating remote work, educational pursuits, and social interactions, thereby mitigating the repercussions of physical distancing and the dearth of traditional face-to-face engagements in the tangible world. By the end of 2023, the number of video game players is expected to exceed 3 billion (Boldi et al., 2022). According to a proposal by the International Monetary Fund (IMF), the contagious disease COVID-19 triggered a very distinct economic crisis from the past. The difference lies in its multifaceted and unpredictable nature, while simultaneously having a profound impact on the entire world (Mazur et al., 2021).

This paper aims to analyse how the COVID-19 pandemic influenced the stock prices of companies, which is a critical area of study given the pandemic's unprecedented impact on global financial markets. Recent studies have extensively explored the relationship between health crises and stock market performance. For instance, Yilanci & Pata (2023) employed wavelet-based analysis to examine the impact of COVID-19 on stock prices, exchange rates, and sovereign bonds in Brazil and India, finding significant correlations between COVID-19 cases and stock prices in both countries, particularly in high-frequency ranges. Similarly, Teitler & Tavor (2024) conducted a comparative study on the varied impact of COVID-19 on stock markets in low- and high-infection-rate countries, highlighting the importance of country-specific strategies and policies to mitigate the pandemic's effects. Fasanya et al. (2023) explored the effects of the pandemic on stock indices in the USA, France, China, and Italy, using an autoregressive distributed lag (ARDL) model, and found significant short-term and long-term impacts, with variations across different countries. Another study by Mamilla et al. (2023) utilized GARCH models to examine the volatility of nine National Stock Exchange indices before, during, and after the pandemic, concluding that COVID-19 significantly increased market volatility and risk, affecting investor returns.

The endeavour to forecast stock market prices stands as a pivotal objective within both scientific inquiry and business endeavours. Traditionally, a significant focal point of research has been the modelling of time series data (Stefko et al., 2022). The COVID-19 pandemic inflicted considerable adverse effects on stock markets, particularly in its initial stages, as it posed severe threats to public health and overall safety. To scrutinize the correlation between the weekly stock prices of the selected companies and the weekly tally of new COVID-19 cases, we employ a VAR (Vector Autoregression) model. Aliu et al. (2023) utilized a VAR model with impulse response functions, variance decomposition, Granger causality test, and vector error correction model to examine the impact of the Russian invasion of Ukraine, which accelerated the growth of agricultural commodity prices and heightened global food uncertainties. Hossain et al. (2021) investigated the statistical influence of COVID-19 on intraday momentum of S&P500 and CSI300. Additionally, they employed the predictability of time-conditioned strategies to forecast intraday momentum of stock returns. Vochozka et al. (2020) explored the extent to which fluctuations in oil prices affect the value of the Euro against the US Dollar. They conducted a regression analysis using neural networks, based on 10,000 networks generated for each experimental combination. The research followed a consistent procedure with incremental variations of a single parameter across time frames (1, 5, 10, and 30 days). Podhorska et al. (2019) used an econometric model created through multiple regression to identify a significant source of valuation and verification of corporate goodwill. Gavurová et al. (2017), on the other hand, conducted a multilevel logistic regression analysis to describe the temporal trend, age, and gender distribution of diabetes-related deaths as a significant component of endocrine, nutritional, and metabolic diseases. When selecting methods for future value prediction, both the static models and fuzzy logic are employed. The choice of method depends on the specific situation and data analysis requirements. Fuzzy logic allows, to some extent, addressing the issue of insufficient knowledge by providing a straightforward way to reach a conclusion based on unclear, imprecise, or missing input data (Polishchuk et al., 2019). Hašková (2021) introduces a general fuzzy algorithm formulated within Zadeh's fuzzy approach for solving predictive economic problems under the conditions of internal uncertainty of the model and external uncertainty of related conditions using input data. Building upon prior research, Hašková et al. (2023) introduce a forward-looking analysis utilizing a fuzzy multi-criteria evaluation framework. This system, grounded in a non-fuzzy neural methodology, showcases the ability to incorporate a learning mechanism and handle ambiguous concepts. Nowak & Romaniuk (2014) address the issue of evaluating European options when the underlying asset follows a geometric Levy process. Using stochastic analysis and fuzzy theory, formulas for the valuation of European call and put options are derived when employing ESMM and MCMM. The proof of these valuation formulas and the presentation of certain numerical option pricing analyses are conducted within a fuzzy environment in the financial market. Hašková et al. (2023) propose that while a fuzzy neural network demonstrates efficiency in solving prediction problems with input data, offering quicker outputs than a traditional fuzzy system, it remains more accessible. However, they argue that a well-informed and experienced expert may achieve faster convergence in the learning process using a fuzzy system, especially with a minimal range of input data containing essential information. Therefore, the fuzzy system emerges as a potential alternative to a fuzzy neural network in predictive tasks (Hašková et al., 2023). Over the past fifty years, a history of macroeconomic forecasts and their accuracies has been established. Economists do not agree on how the economy operates, and these disagreements are reflected, among other things, in the specification of relationships in macroeconomic models. However, over time, no single approach has yielded better predictive results than any other (Nyman & Ormerod, 2017).

This study uniquely contributes to the empirical literature by utilizing a VAR model to analyse the impact of the COVID-19 pandemic on the stock prices of leading video game companies. While previous studies have explored the broader economic impacts of the pandemic (Kim, 2021; Liu et al., 2020), our research is distinct in its focus on the video game sector and its granular analysis of specific firms such as Electronic Arts, Ubisoft, Square Enix, Nintendo, Sony, and Activision Blizzard.

2. Methodology

For the purposes of this research, data on stock prices of video game companies Electronic Arts, Ubisoft, Square Enix, Nintendo, Sony, and Activision Blizzard were collected. Data from the period of January 1, 2020, to August 2, 2023, was obtained from the Yahoo Finance website (Yahoo! Finance, 2023). The data set includes information about the weekly closing, maximum, and minimum stock prices, as well as data on the volume of their sales. The basic descriptive statistics of the data set containing weekly closing stock prices are presented in Table 1. Stock prices are retained in their respective currencies, namely US Dollars for Electronic Arts and Activision Blizzard, Euros for Ubisoft, and Japanese Yen for Square Enix, Sony, and Nintendo.

Table 1. ADF test results.

Variables	Mean	Sd	Se	Median	Min	Max	Skew	Kurtosis
Activision Blizzard	77.75	9.87	0.72	77.79	52.92	100.77	-0.21	-0.03
Electronic Arts	127.46	10.89	0.79	127.32	92.88	146.92	-0.61	0.12
Ubisoft	50.96	19.05	1.39	50.12	18.93	84.30	-0.04	-1.26
Sony	10633.36	2111.43	153.58	11149.96	5708.52	14823.13	-0.45	-0.61
Nintendo	4917.51	798.49	58.08	5026.31	2786.26	6519.00	-0.54	-0.12
Squre Enix	5819.05	623.24	45.33	5962.62	3996.23	7540.00	-0.54	0.07

Source: Authors using package "psych" in RStudio.

The descriptive statistics include the mean, standard deviation, standard error, median, minimum and maximum values, skewness coefficient, and kurtosis coefficient. Furthermore, the values of weekly new COVID-19 cases have been collected from the beginning of the pandemic, covering the period from January 8, 2020, to August 2, 2023. The dataset containing these values was downloaded from the Our World in Data website (Our World in Data, 2023). For analysis, the time series of new COVID-19 cases was adjusted to reflect the percentage changes in weekly counts. This adjustment was made to normalize the data and capture the relative growth or decline in new cases. The percentage change for each week was calculated as follows:

$$\text{Percentage Change} = \left(\frac{\text{Current Week Cases - Previous Week Cases}}{\text{Previous Week Cases}}\right) \times 100 \tag{1}$$

Both the new weekly COVID-19 cases and their percentage changes are depicted in the graphs in Figure 1.

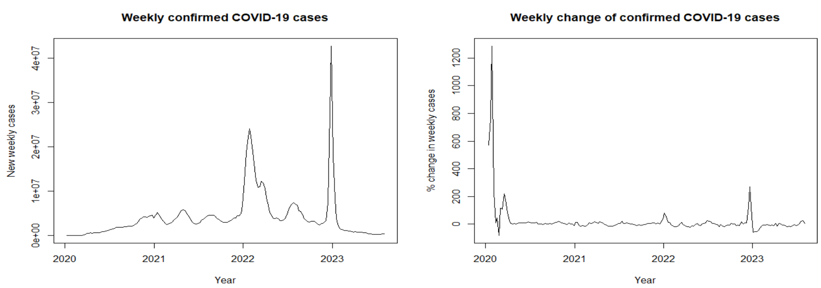

Figure 1. Weekly confirmed COVID-19 cases.
Source: Authors using RStudio.

VAR (Vector Autoregressive) model is a statistical tool used for the analysis and prediction of time series, particularly for multivariate data. It's a system of equations in which variables in time series mutually influence each other through their previous values and the values of other variables in the system. The VAR model enables capturing complex dynamic relationships between variables and temporal dependencies, making it a valuable instrument for econometric analysis, macroeconomic forecasting, financial market analysis, assessment of financial crises, and macroeconomic and monetary shocks (Feng et al., 2021). In this study, VAR models will be created for individual time series of weekly closing prices of investigated video game companies' stocks, along with the adjusted time series of new weekly COVID-19 cases. The general formula for the VAR model is as follows:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t \qquad (2)$$

where y_t represents a vector of length k, containing the values of variables at time t, c is a constant vector, A_p is a matrix of autoregressive coefficients for the given lag with dimensions k x k, e_t is a vector of errors with a zero mean.

An essential step in creating a VAR model is determining the optimal number of lags (p), which specifies the number of past values to be included in the model. The optimal lag length was determined using several information criteria, including the Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQ), the Schwarz Information Criterion (SC), and the Final Prediction Error (FPE). These criteria were computed using the 'VARselect' function in RStudio, which evaluates different lag lengths and selects the model with the lowest values for these criteria. The information criteria are calculated as follows:

$$AIC(n) = \ln \det(\Sigma_u(n)) + \frac{2}{T} n K^2 \qquad (3)$$

$$HQ(n) = \ln \det(\Sigma_u(n)) + \frac{2\ln(\ln(T))}{T} n K^2 \qquad (4)$$

$$SC(n) = \ln \det(\Sigma_u(n)) + \frac{\ln(T))}{T} n K^2 \qquad (5)$$

$$FPE(n) = \left(\frac{T + n^*}{T - n^*}\right)^K \det(\Sigma_u(n)) \qquad (6)$$

where $\Sigma_u(n)$ is the estimated covariance matrix of the residuals for a model with lag order n, T is the sample size, K is the number of equations in the system, n is the lag order, $n*$ is the total number of parameters in each equation.

The model with the lowest values for these criteria was selected as it indicates a better fit with a balance between model complexity and goodness of fit. Typically, a lower number of lags results in a simpler model, while a higher number of lags can better capture the dynamic relationships but may lead to overfitting. The selected number of lags influences the model's accuracy and reliability by determining how well it can capture the temporal dependencies in the data without introducing unnecessary complexity.

Creating a VAR model requires data stationarity, which will be verified using the Augmented Dickey-Fuller test (ADF), where the p-value must be lower than 5% to confirm stationarity. The 'tseries' package in RStudio will be utilized for this purpose. If stationarity is rejected, the time series will be transformed into a stationary series through differencing, which is a mathematical technique commonly used in time series analysis to stabilize non-stationary data. Differencing involves calculating the differences between consecutive terms in a sequence. By doing so, the original data's fluctuations around its trends or patterns are emphasized, making the data more suitable for statistical analyses that assume stationarity. Another essential characteristic of the VAR model is its stability. Stability implies that the model exhibits consistent and predictable behaviour over time. Stability is verified by computing the roots of the characteristic polynomial of the VAR model. If all the roots are inside the unit circle, the model is stable, signifying that the variables will gradually return to the long-term equilibrium state after a sudden shock or change. In RStudio, we can assess the stability of the VAR model using the 'roots' function. This function calculates the roots of the characteristic polynomial. If all the polynomial's roots are within the unit circle (with absolute values less than 1), the model is stable.

Individual VAR models will be interpreted using the Impulse Response Function (IRF), which illustrates how one variable responds to a unit impulse (a sudden change of magnitude one) in another variable within the system over time. This approach will reveal the impact of a unit impulse in the variation of weekly COVID-19 case counts on the stock prices of the investigated video game companies.

3. Research results

For the verification of data stationarity, the Augmented Dickey-Fuller test was applied to the time series, and its results are recorded in Table 2. The first column examines stationarity on the unadjusted weekly closing stock prices. Here, stationarity is only met by the time series of Square Enix company. Therefore, the data underwent initial differencing. After the initial differencing, all time series exhibit stationarity.

Table 1. Augmented Dickey-Fuller test.

Variables	Closed price		In first difference	
	Dickey-Fuller	P-Value	Dickey-Fuller	P-Value
ACTIVISION BLIZZARD	-2.1813	0.5004	-10.142	0.01
ELECTRONIC ARTS	-3.0140	0.1521	-9.9744	0.01
UBISOFT	-3.0695	0.1289	-9.6926	0.01
SONY	-2.1402	0.5175	-8.9416	0.01
NINTENDO	-2.5121	0.3620	-9.9555	0.01
SQUARE ENIX	-3.7352	0.0236	-9.5933	0.01

Source: Authors using package "tseries" in RStudio.

The optimal number of lags was determined by comparing the information criteria AIC, HQ, SC, and FPE. The information criteria are presented in Table 3.

Table 2. Optimal lag testing.

Activision Blizzard								
Lags	1	2	3	4	5	6	7	8
AIC(n)	8.4889	**8.3737**	8.3780	8.3965	8.4226	8.4649	8.5083	8.5399
HQ(n)	8.5327	**8.4467**	8.4803	8.5280	8.5833	8.6548	8.7275	8.7883
SC(n)	8.5970	**8.5538**	8.6302	8.7208	8.8189	8.9332	9.0487	9.1524
FPE(n)	4861	**4332**	4351	4432	4550	4748	4960	5121
Electronic Arts								
Lags	1	2	3	4	5	6	7	8
AIC(n)	9.4274	**9.3062**	9.3098	9.3274	9.3186	9.3545	9.3858	9.4217
HQ(n)	9.4712	**9.3793**	9.4120	9.4589	9.4794	9.5445	9.6050	9.6701
SC(n)	9.5354	**9.4864**	9.5619	9.6517	9.7149	9.8229	9.9262	10.0342
FPE(n)	12424	**11007**	11046	11244	11147	11557	11928	12368
Ubisoft								
Lags	1	2	3	4	5	6	7	8
AIC(n)	8.1192	**8.0046**	8.0185	8.0272	8.0536	8.0928	8.0817	8.1073
HQ(n)	8.1630	**8.0776**	8.1208	8.1587	8.2144	8.2828	8.3009	8.3557
SC(n)	8.2273	**8.1847**	8.2707	8.3515	8.4500	8.5612	8.6221	8.7198
FPE(n)	3358	**2995**	3037	3064	3146	3273	3237	3323
Sony								
Lags	1	2	3	4	5	6	7	8
AIC(n)	18.4532	18.3407	**18.3396**	18.3544	18.3949	18.4370	18.4645	18.4762
HQ(n)	18.4971	**18.4137**	18.4419	18.4859	18.5556	18.6270	18.6837	18.7246
SC(n)	18.5613	**18.5208**	18.5918	18.6786	18.7912	18.9054	19.0049	19.0887
FPE(n)	1.03E+08	9.23E+07	**9.22E+07**	9.36E+07	9.75E+07	1.02E+08	1.05E+08	1.06E+08
Nintendo								
Lags	1	2	3	4	5	6	7	8
AIC(n)	16.7123	**16.5857**	16.6035	16.6274	16.6522	16.6917	16.7185	16.7196

HQ(n)	16.7562	**16.6588**	16.7058	16.7589	16.8129	16.8817	16.9377	16.9680
SC(n)	16.8204	**16.7659**	16.8557	16.9517	17.0485	17.1601	17.2590	17.3321
FPE(n)	1.81E+07	**1.60E+07**	1.62E+07	1.66E+07	1.71E+07	1.78E+07	1.82E+07	1.83E+07
Square Enix								
Lags	1	2	3	4	5	6	7	8
AIC(n)	17.4419	17.3239	**17.2847**	17.2848	17.3194	17.3471	17.3849	17.4117
HQ(n)	17.4858	17.3969	**17.3870**	17.4163	17.4801	17.5371	17.6041	17.6601
SC(n)	17.5500	**17.5040**	17.5369	17.6090	17.7157	17.8155	17.9254	18.0242
FPE(n)	3.76E+07	3.34E+07	**3.21E+07**	3.21E+07	3.33E+07	3.42E+07	3.55E+07	3.65E+07

Source: Authors using RStudio.

From Table 3, it can be observed that the optimal number of lags for the majority of time series is two lags. Companies Activision Blizzard, Electronic Arts, Ubisoft, and Nintendo exhibit the lowest information criteria and errors at this lag level. For companies Sony and Square Enix, the results are inconclusive. Considering a lower predictive error, VAR models with three lags will be created, while for the others, models with two lags will be established.

To examine the impact of sudden changes in the number of new COVID-19 infections on the weekly stock prices of video game companies, we employed the Impulse-Response Function (IRF). The resulting functions are depicted graphically in Figure 2.

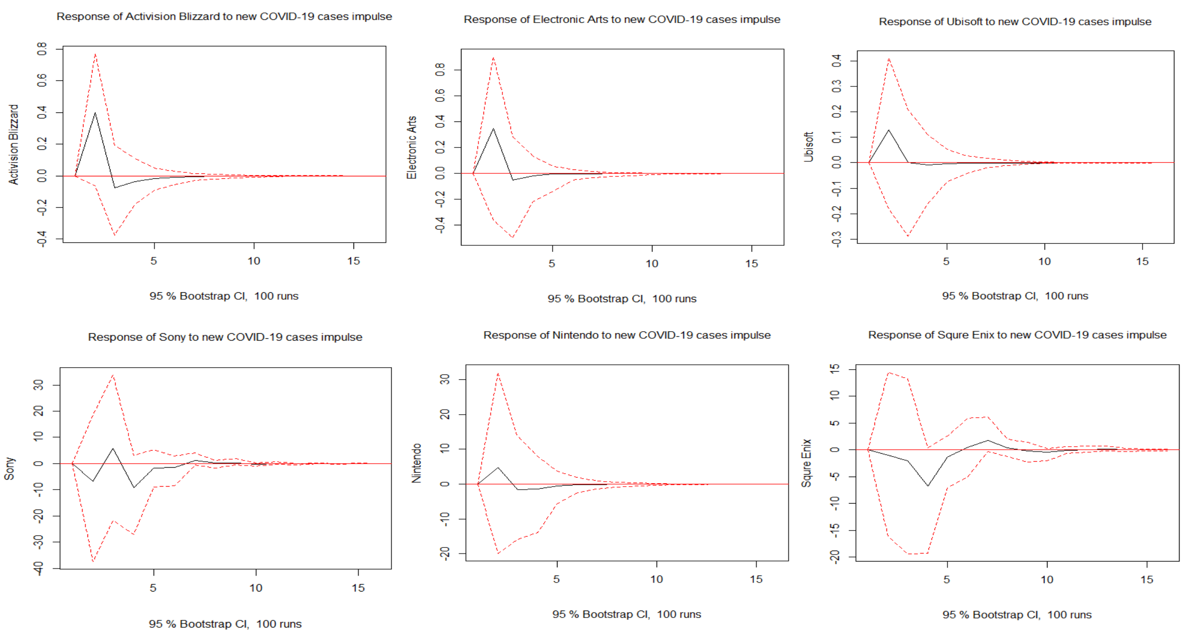

Figure 2. Impulse-response functions.
Source: Authors using RStudio.

In these graphs, the black (solid) lines represent the anticipated responses in stock prices to a one-time impulse in the change of new COVID-19 cases, while the red (dashed) lines indicate the level of model certainty.

From the graphs, it can be observed that the VAR models for Activision Blizzard, Electronic Arts, Ubisoft, and Nintendo exhibit greater confidence in the positive effect of a one-time impulse in case counts. In contrast, companies like Sony and Square Enix show more uncertainty regarding the impact of the impulse. Activision Blizzard demonstrates the most positive response to the new case count. Along with Electronic Arts, Ubisoft, and Nintendo, it anticipates a slight decrease in stock prices following an initial surge. This suggests that the stock values of these companies responded more favourably to the increase in new COVID-19 cases.

This favourable response can be attributed to these companies capitalizing on the heightened demand for digital entertainment as consumers sought indoor activities during lockdowns. Financially, this surge in demand translated to increased revenues, higher profit margins, and boosted investor confidence, making their stocks more attractive and stable investments during the crisis. Overall, the expected impact of the impulse on company prices diminishes and fades within seven weeks of the initial impulse. However, for Sony and Square Enix, whose VAR models were constructed with three lags, the impact shows more fluctuations and uncertainty.

The stability of the model was determined by calculating the roots of the characteristic polynomial for the VAR model. These calculations are documented in Table 4. The results in the table demonstrate that none of the variables exceeded the value of 1, thus we can consider the models as stable.

Table 3. VAR models stability.

Variables	1	2	3	4	5	6
Activision Blizzard	0.544447	0.203358	0.203358	0.154449		
Electronic Arts	0.536150	0.137592	0.137592	0.083726		
Ubisoft	0.512740	0.182413	0.182413	0.144241		
Sony	0.530157	0.523529	0.523529	0.248878	0.138843	0.138843
Nintendo	0.529865	0.229648	0.229648	0.043895		
Square Enix	0.635350	0.635350	0.605287	0.162568	0.138514	0.138514

Source: Authors using RStudio.

4. Discussion

The COVID-19 pandemic had a unique impact on the video game industry compared to other global sectors. One reason for this could be the virtual nature of the industry. Physical copies of games are no longer necessary, as players can purchase and download games from their homes, minimizing the risk of disease exposure. Despite this, our study found differences in how various companies were affected, likely due to their geographical locations.

Western companies, with their global player bases, generally responded more positively to the increase in COVID-19 cases. For example, Şener et al. (2021) observed a significant rise in player engagement and game sales during the pandemic. This aligns with our findings that companies like Activision Blizzard, Electronic Arts, and Ubisoft benefitted from the higher demand. Among these, Ubisoft showed the most uncertainty and the least positive response, possibly due to its struggling stock prices.

Japanese companies like Sony, Nintendo, and Square Enix had different reactions to the pandemic. Nintendo's response was similar to Western companies but with higher uncertainty and a weaker positive response. This might be because of their strong presence in the global market and loyal fan communities, even among non-Asian players. Square Enix, despite being popular in the West, focuses on Asian aesthetics and gameplay, resulting in a primarily Asian fanbase. This could explain the longer-lasting negative impact of COVID-19 on their stock prices. Sony, a major player in both game development and console manufacturing, showed minor fluctuations in stock prices due to COVID-19. This might be because of their dual focus on games and the launch of the PlayStation 5 during a global chip shortage, affecting their stock prices.

Kim (2021) noted that video game industry revenues surpassed those of the film industry early in the pandemic due to increased home confinement. Our study supports this by showing that the demand for digital entertainment helped buffer the economic downturn. Our analysis adds depth by illustrating how different companies responded to this demand. While many traditional markets faced severe downturns, the video game industry provided a unique refuge for consumers and businesses. Its digital nature allowed continued operations and even expansion during lockdowns and social distancing measures.

This resilience is reflected in the rising stock prices of companies like Activision Blizzard and Electronic Arts, which capitalized on the increased demand for home entertainment. The pandemic drove consumers to seek new forms of engagement, leading to a boom in video game sales and player engagement. As Szopik-Depczyńska et al. (2020) noted, the industry's ability to diversify and attract new players and companies was crucial to its strong performance. This diversification not only sustained the industry during the crisis but also highlighted its potential for continued growth and innovation.

Conclusions

The COVID-19 pandemic has had a significant impact on various sectors, including the global video game industry. This study has investigated how the pandemic influenced the stock prices of leading video game companies such as Electronic Arts, Ubisoft, Square Enix, Nintendo, Sony, and Activision Blizzard using a Vector Autoregression (VAR) model. Our analysis revealed that Western companies, such as Activision Blizzard and Electronic Arts, showed more positive responses to changes in COVID-19 case numbers compared to their Eastern counterparts like Sony and Square Enix. This could be attributed to the fact that video game companies in Western countries have their player communities extending beyond Asian players.

This research contributes to the understanding of market dynamics and investor behaviour in the face of global crises. By focusing on a sector that blends technology and entertainment, this research bridges gaps in contemporary literature, offering new perspectives on how digital industries can serve as economic buffers. The findings highlight the video game industry's potential as a resilient sector during economic downturns, offering valuable insights for investors and policymakers.

However, it is important to acknowledge the limitations of this study. The research focused primarily on the impact of COVID-19 without considering other concurrent factors that might have influenced the video game industry, such as technological advancements or changes in consumer behaviour unrelated to the pandemic. Additionally, the data analysis was limited to publicly available stock prices and COVID-19 case numbers, which may not capture the full complexity of market dynamics. Future research should explore these additional factors and their interplay with global health crises to provide a more comprehensive understanding of the video game industry's evolution. Investigating the long-term impacts of the pandemic on consumer behaviour and market strategies within the video game industry could also offer valuable insights for policymakers and investors.

In conclusion, while the video game industry has demonstrated notable resilience during the COVID-19 pandemic, ongoing research and policy support are essential to sustain and enhance this sector's growth and stability in the face of future global challenges.

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The Role of Foreign Workers in the Evolution of Employment in the Construction Sector: A Comparative Analysis of Selected Central European Countries

Michal Kot [1]

[1] Czestochowa University of Technology, Poland
ORCID: 0000-0002-5449-593X
e-mail: michal.kot@pcz.pl

Abstract

The article brings a novel perspective, integrating a comparative analysis of six countries (Poland, Czech Republic, Slovakia, Hungary, Lithuania, and Germany) with the impact of contemporary crises (the pandemic, the war in Ukraine) and the Green Deal on the role of migrants in construction. Its uniqueness lies in capturing the evolution of migrants from cheap labour to skilled professionals in a regional context. The goal of the study is to identify and compare the impact of foreign workers on employment in the construction sector between 2014 and 2024, to provide data for migration and integration policies and projections for the future of the region in the face of demographic and economic challenges. The methodology is based on a mixed approach: quantitative (statistical analysis of data from the CSO, Eurostat, OECD, and national offices) and predictive (extrapolation of trends to 2030). Data for 2024 were estimated based on trends from 2014–2023, considering migration, policies, and demand for skills in sustainable construction. The research sample covers the construction sector in six Central European countries, with a focus on migrants' employment (legal and illegal), their qualification structure, and migration policies. The results show a significant increase in the number of migrants: in Poland by 150% (47,000 to 140,000) and in Germany by 66.7% (278,000 to 504,000), driven by investment and the influx of Ukrainians. The employment structure is evolving – in Poland, the proportion of unskilled workers fell from 75% to 60%, while specialists rose from 5% to 10%. Projections show further growth (Poland: 160,000; Germany: 550,000 by 2030). Liberal policies (e.g. Poland +156%) are more effective in increasing migrant contributions than restrictive ones (Hungary +117%). Recommendations include simplification of procedures, training and integration, and strengthening the role of migrants in sector transformation.

Key words

foreign workers, labour migration, construction sector, employment, migration policy, Central Europe.

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Introduction

The construction sector in Central European countries has undergone a dynamic transformation over the past decade, determined by growing demand for infrastructure and resource upgrades in countries such as Poland, the Czech Republic, Slovakia, Hungary, Lithuania, and Germany. These investments, supported by EU funds such as NextGenerationEU and national pandemic recovery programmes, have increased pressure on labour markets facing local labour shortages (Eurostat, 2023). Aging populations, emigration to the West, and a decline in the number of technical graduates are further exacerbating these deficits (OECD, 2022). In this context, foreign workers have become a key pillar of the sector, enabling ambitious projects such as highways, housing developments, factories and renewable energy sources in line with the European Green Deal (Hainsch et al., 2022). Their role increased after the COVID-19 pandemic, which disrupted supply chains and revealed construction's reliance on a mobile workforce (Frey & Osborne, 2020). Since 2022, the war in Ukraine has accelerated the influx of Ukrainians, changing employment dynamics in the region (Kamyshnykova, 2023). Globally, migrants have long driven major investments – in the United Arab Emirates they have built modern metropolises, in Qatar they have erected infrastructure for international sporting events, and in Singapore they have transformed the city into Asia's financial centre, highlighting their transformative potential (Wagle, 2024).

The literature indicates that labour migration alleviates labour shortages, but raises challenges related to integration, regulation, and social costs (Anderson et al., 2021). In Central Europe, the importance of migrants is particularly evident in the face of the energy crisis, which is driving up the price of construction materials and increasing the need for rapid infrastructure projects (Jakovljevic et al., 2021). In Poland and the Czech Republic, for example, migrants are supporting an investment boom, while in Germany, immigration policies are attracting professionals from the region (Schäfer & Henn, 2023). Current events, such as Brexit, tighter post-pandemic border controls, and sanctions related to the war in Ukraine, are complicating migration flows, affecting the availability of workers (Portes & Springford, 2023). At the same time, the Green Deal requires new skills, putting migrants at the centre of the sector's transformation (European Commission, 2023). Their role in construction goes beyond mere employment – they are a driver of economic resilience in times of crisis (Alessi et al., 2020).

Interest in the topic stems from the construction sector in Central European countries and its growing reliance on migrants to enable continued investment in the face of demographic, economic, and geopolitical challenges such as war and the pandemic. Their importance, while globally recognised, needs to be better understood in a regional context.

The literature focuses on the overall effects of migration (Borjas, 2019) or the impact of automation on the construction industry (Frey & Osborne, 2020), but there is a lack of detailed comparative analyses of the role of foreign workers in the construction sector in Central Europe, especially in the context of their contribution to employment in times of current crises and the Green Deal.

The goal is to identify and compare the impact of foreign workers on employment in the construction sector in Poland, the Czech Republic, Slovakia, Hungary, Lithuania, and Germany between 2014 and 2024 to provide data for migration and integration policies in the face of contemporary challenges. We examine how migrants are shaping the labour market and what this means for the region's future. Research Questions:

1. How have foreign migrants affected the dynamics of construction employment in Central Europe between 2014 and 2024?
2. What are the differences in the role and impact of migrants between countries in the region in the context of current events?
3. What policies and social strategies can increase the contribution of migrants to the construction sector in the face of contemporary challenges?

1. Literature Review

1.1 Theoretical basis of labour migration in the context of construction

Labour migration in the construction sector is well established in the literature through a variety of theoretical frameworks. The push-pull model (Lee, 1966) is a starting point, but Seemann et al., (2021) extends it to include institutional factors such as migration policies and differences in labour standards, which gained prominence after the COVID-19 pandemic. Neoclassical migration theory (Harris & Todaro, 1970) emphasizes income differences as a motivation, which Kamyshnykova (2023) relate to the influx of Ukrainians after 2022 in response to the war. Labour market segmentation theory (Felbo-Kolding et al., 2019) indicates that migrants occupy segments with high demand for unskilled labour, which Schäfer& Henn (2023) confirm in Central European construction. Wallerstein's (1974) dependency theory suggests that migration from peripheral countries supports the development of more advanced economies, which Gereffi (2019) links to the global flow of labour to infrastructure sectors.

De Haas's et al. (2019) institutional approach emphasizes the role of recruitment agencies and social networks in directing migrants to construction, as Kurekova and Zilincikova (2023) observe in the influx of workers from Eastern Europe. Stoklosa et al., (2021) point to the risk of exploitation due to information asymmetries, which ILO (2023) reports confirms in the context of difficult post-pandemic working conditions. Anderson et al., (2021) introduce a complementarity perspective, suggesting that migrants complement the local labour force, increasing sector productivity, which is key to the Green Deal (Hainsch et al., 2022). Vasyltsiv et al., (2023) add that migration increases the flexibility of labour markets, which helps absorb economic shocks such as the energy crisis (Jakovljevic et al., 2021). These theories form a solid basis for analysing the role of migrants in construction in the face of contemporary challenges.

1.2 Historical and contemporary importance of migrants in the construction industry

Historically, migrants have played a key role in construction. In the 19th-century United States, Irish and Chinese labourers-built railroads and canals, fuelling infrastructure development under difficult conditions (Wan, 2022). In post-war Germany, Turkish "guest workers" rebuilt cities in the 1960s and 1970s (Chin, 2019), and in Australia, migrants from Italy and Greece erected power plants and highways in the 1950s and 1960s (Dellios, 2020). Today, Latin American migrants in the US are boosting construction productivity, which Caiumi & Peri (2024) attributes to their ability to alleviate labour shortages. In the UK, after the 2004 EU enlargement, migrants from Central and Eastern Europe dominated the construction sector, especially in London, although Brexit has changed these dynamics (Portes & Springford 2023). In the Gulf countries, Asian migrants are building metropolises, albeit under difficult conditions, which Wagle. (2024) link to global inequalities.

In Central Europe, migrants are key in responding to current events (Cabinova et al., 2024; Surya et al., 2024). The war in Ukraine has increased the influx of Ukrainians, which Kamyshnykova (2023) describe as a "supply shock" to construction, supporting infrastructure projects. The COVID-19 pandemic revealed the sector's reliance on migrants when travel restrictions halted construction (Frey & Osborne, 2020). The energy crisis raised the cost of materials, which increased pressure to quickly complete projects where migrants play a key role (Eurostat, 2023). King et al. (2020) emphasize that migrants mitigate the effects of aging populations, and Vasyltsiv et al., (2023) point out that their presence increases the sector's flexibility during periods of economic instability, which is important in the era of the Green Deal (European Commission, 2023).

1.3 Socio-economic aspects of migration in the construction industry

The economic impact of migration in the construction industry is complex (Owusu et al., 2023). Borjas (2019) suggests that migrants may lower wages for local workers in the short term, but Marois et al. (2020) argue that they increase productivity in the sector in the long term, as evidenced by data from Central Europe. Hack-Polay (2020) points to integration challenges - migrants create ethnic enclaves, which facilitates adaptation but hinders advancement, as Favell (2019) observes in the region. Migration policies are key: Fox-Rush & Rush (2022) note that liberal regulations increase labour supply, but without integration lead to inequality, a trend that intensified after 2022 (Kurekova & Zilincikova, 2023). Migrants bring a diversity of skills, which Knudsen et al., (2023) link to innovation, such as in the sustainable construction required by the Green Deal (Hainsch et al., 2023).

IOM (2023) stresses that improving migrant labour conditions is essential, especially after the pandemic and war in Ukraine, which has increased pressure on labour markets. Gavonel et al., (2021) point out that migration reflects global inequality, which requires sustainable policies. For example, the influx of Ukrainians after 2022 increased competition in the labour market, but also accelerated infrastructure projects (Kamyshnykova, 2023; Tiutiunyk et al., 2024). Tightening migration policies after Brexit and the pandemic further complicate the situation (Ciupijus et al., 2023). Migrants are thus not only a labour force, but also a social and economic factor shaping the future of construction (Oumansour & M'ssiyah, 2024; Korcsmaros et al., 2024).

2. Methodology

The study aimed to analyse the impact of foreign workers on employment in the construction sector in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany between 2014 and 2024, assess future trends until 2030, and develop recommendations for migration and integration policies in the context of challenges such as the Green Deal and labour shortages. A mixed approach was used: quantitative and predictive.

The quantitative part used data from the CSO, Eurostat, OECD and national statistical offices (CSU, SUSR, KSH, Statistics Lithuania, Destatis), supplemented by reports from PIP, EURES, Spectis and IOM. Data included employment, share of foreigners and number of companies. Values for 2024 were estimated extrapolating trends from 2014-2023 (no complete data available as of February 28, 2025). The analysis was based on statistical methods: dynamics of change and cross-country comparisons, with results in tables. For the projections (2024-2030), extrapolation of trends was used, taking into account stabilization of migration, automation and demand for RES qualifications (Table 10). Analysis of migration policies (Table 8) was used for recommendations.

A quantitative approach was chosen for comparability of data, complemented by forecasts and policy assessments to answer research questions and propose strategies to enhance the role of migrants. Limitations include estimates for 2024 and incomplete data on the shadow economy, although reliable sources provided a solid base.

The objective was expanded beyond analysis to include: (1) identification of the impact of migrants, (2) projections of employment trends, and (3) recommendations for policies to support the construction sector. The study provides data and practical guidance for the future of the region, consistent with the full research process.

3. Research Results

The dynamics of change in the number of construction companies in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany from 2014 to 2024 are shown below. The figures reflect the evolution of the construction sector in these countries, taking into account both the impact of economic factors, such as infrastructure investments and EU funds, and social factors, including migration and demographic changes. The period 2014-2024 allows an assessment of long-term trends in the Central European region, where the construction sector plays a key role in the economy. The values for 2024 are estimates, based on extrapolation of trends from previous years, as full statistics for that year are not yet available (as of February 26, 2025). The information includes both numerical changes (in thousands) and percentage changes, making it easier to compare the growth or decline in the number of companies between countries (Table 1).

Table 1. Dynamics of change in the number of construction companies in selected Central European Countries (2014–2024).

Country	2014 (thousands)	2016 (thousands)	2018 (thousands)	2020 (thousands)	2022 (thousands)	2024* (thousands)	Change 2014-2024 (%)
Poland	89.0	90.2	91.5	92.5	95.2	96.8	+8.76%
Czech Republic	51.5	52.0	52.5	53.0	54.1	55.0	+6.80%
Slovakia	18.5	18.8	19.2	19.8	20.3	20.7	+11.89%
Hungary	36.8	37.2	37.8	38.2	39.0	39.6	+7.61%
Lithuania	11.8	12.0	12.2	12.4	12.8	13.0	+10.17%
Germany	77.0	77.8	78.5	79.5	80.8	82.2	+6.75%

Note: * – estimated.

Source: Central Statistical Office (2024c); Czech Statistical Office (2023b); Statistical Office of Slovakia (2023b); Hungarian Statistical Office (2023b); Statistics Lithuania (2023a); Destatis (2024b); Eurostat (2024e); Spectis (2024a).

Between 2014 and 2024, the number of construction companies increased in all the Central European countries analysed. Slovakia recorded the highest percentage growth (+11.89%), increasing the number of companies from 18.5 thousand to 20.7 thousand, Lithuania achieved +10.17% (from 11.8 thousand to 13.0 thousand), and Poland +8.76% (from 89.0 thousand to 96.8 thousand), showing the largest numerical increase (+7.8 thousand). Hungary recorded an increase of +7.61% (from 36.8 thousand to 39.6 thousand), the Czech Republic +6.80% (from 51.5 thousand to 55.0 thousand), and Germany +6.75% (from 77.0 thousand to 82.2 thousand), with the second largest numerical increase (+5.2 thousand). The aggregate conclusions point to positive dynamics in the region, driven by infrastructure investment, EU funds and migration, although the scale and pace of growth vary depending on local economic and demographic conditions.

Legal employment in the construction sector in Poland, the Czech Republic, Slovakia, Hungary, Germany and Lithuania from 2014 to 2024, along with the percentage dynamics of change, is presented below based on estimates and data from national statistical offices (Table 2).

Table 2. Legal employment in the construction sector in selected Central European Countries (2014-2024) and the dynamics of change.

Country	Legal employment 2014 (thousands)	Legal employment 2024 last quarter (thousands)	Dynamics of change 2014-2024 (%)	Sources of information
Poland	440	510	+15.9%	CSO, Eurostat, PIP reports
Czech Republic	245	265	+8.2%	CSU, Eurostat, EURES reports
Slovakia	125	135	+8.0%	SUSR, Eurostat
Hungary	195	205	+5.1%	CCC, Eurostat
Lithuania	72	67	-6.9%	Statistics Lithuania, Eurostat
Germany	2280	2420	+6.1%	Destatis, Eurostat, Bundesagentur für Arbeit reports

Source: Central Statistical Office (2024d); State Labour Inspectorate (2023); Czech Statistical Office (2023b); Statistical Office of Slovakia (2023b); Hungarian Statistical Office (2023b); Statistics Lithuania (2023a); Destatis (2024b); Eurostat (2024a).

Poland recorded the highest employment growth (+15.9%), thanks to infrastructure investments and an influx of migrants. The Czech Republic (+8.2%) and Slovakia (+8.0%) showed stable growth, driven by EU funds. Hungary (+5.1%) grew at a slower pace due to labour outflows. Germany (+6.1%) increased employment due to labour demand. Lithuania recorded a decline (-6.9%) through emigration. Overall employment (legal and illegal) in the construction sector in selected Central European Countries from 2014 to 2024, along with the dynamics of change and the estimated share of illegal labour, is presented below based on statistical data and reports (Table 3).

Table 3. Employment in the construction sector (legal and illegal) in selected Central European Countries (2014-2024) and the dynamics of change.

Country	Employment (thousands) 2014	Employment (thousands) 2024	Dynamics of change 2014-2024 (%)	Share of illegal employment 2014 (%)	Share of illegal employment 2024 (%)
Poland	470	560	+19.1%	6.4%	8.9%
Czech Republic	255	280	+9.8%	3.9%	5.4%
Slovakia	130	145	+11.5%	3.8%	6.9%
Hungary	205	220	+7.3%	4.9%	6.8%
Lithuania	77	72	-6.5%	6.5%	6.9%
Germany	2320	2520	+8.6%	2.2%	4.0%

Source: Central Statistical Office (2024a); State Labour Inspectorate (2023); Czech Statistical Office (2023b); Statistical Office of Slovakia (2023a); Hungarian Statistical Office (2023a); Statistics Lithuania (2023b); Destatis (2024a); Eurostat (2024c).

Poland stands out with the highest growth (+19.1%), mainly due to a construction boom and a growing shadow economy (from 6.4% to 8.9%). The Czech Republic (+9.8%) and Slovakia (+11.5%) increased employment, including illegals (to 5.4% and 6.9%). Hungary (+7.3%) and Germany (+8.6%) saw moderate growth, with illegal employment rising to 6.8% and 4.0%. Lithuania (-6.5%) lost workers through emigration, with minimal growth in the shadow economy (to 6.9%).

The numerical share of foreigners (in thousands) in legal employment in the construction sector in 2014 and 2024 in the six Central European Countries, along with the percentage change in this share over the decade, is shown below (Table 4).

Table 4. Numerical share of foreigners in legal employment in the construction sector (2014-2024) and dynamics of change.

Country	Share of foreigners 2014 (thousands)	Share of foreigners 2024 (thousands)	Dynamics of change in share of foreigners 2014-2024 (%)
Poland	44	128	+190.9%
Czech Republic	20	40	+100.0%
Slovakia	6	14	+133.3%
Hungary	6	12	+100.0%
Lithuania	3	5	+66.7%
Germany	274	484	+76.6%

Source: Central Statistical Office (2024c); State Labour Inspectorate (2023); Czech Statistical Office (2023a); Statistical Office of Slovakia (2023b); Hungarian Statistical Office (2023a); Statistics Lithuania (2023a); Destatis (2024c); Eurostat (2024b).

Poland recorded the largest increase in the number of legally employed foreigners, from 44,000 in 2014 to 128,000 in 2024 (+190.9%), thanks to simplifications in the employment of migrants, mainly from Ukraine. The Czech Republic doubled the number from 20 thousand to 40 thousand (+100.0%), as did Hungary from 6 thousand to 12 thousand (+100.0%). Slovakia increased its share from 6 thousand to 14 thousand (+133.3%), benefiting from migrants from the region. Germany saw an increase from 274,000 to 484,000 (+76.6%), driven by legal migration from the EU. Lithuania, with the smallest scale, increased from 3,000 to 5,000 (+66.7%), mainly thanks to Belarusians.

Table 5 shows the share of foreigners in total employment (legal and illegal) in the construction sector from 2014 to 2024 in six Central European Countries, along with the dynamics of change in this share. The data is based on migration trends and employment statistics.

Table 5. Dynamics of change in employment of foreigners in the construction sector in selected Central European Countries (2014-2024).

Country	Share of foreigners 2014 (thousands)	Share of foreigners 2024 (thousands)	Dynamics of change in the share of foreigners 2014-2024 (%)
Poland	47	140	+150.0%
Czech Republic	20	42	+87.5%
Slovakia	7	15	+100.0%
Hungary	6	13	+100.0%
Lithuania	3	6	+100.0%
Germany	278	504	+66.7%

Source: Central Statistical Office (2024c); State Labour Inspectorate (2023); Czech Statistical Office (2023b); Statistical Office of Slovakia (2023a); Hungarian Statistical Office (2023b); Statistics Lithuania (2023b); Destatis (2024b); Eurostat (2023).

Poland saw the largest increase in the number of foreigners in the construction sector, from 47 thousand in 2014 to 140 thousand in 2024 (+150.0%), driven by a construction boom and an influx of workers, mainly from Ukraine. The Czech Republic increased from 20 thousand to 42 thousand (+87.5%), benefiting from migration from Eastern Europe. Slovakia doubled its share, from 7,000 to

15,000 (+100.0%), as did Hungary, where it rose from 6,000 to 13,000 (+100.0%), albeit on a smaller scale. Germany, with the largest number of foreigners, saw an increase from 278,000 to 504,000 (+66.7%), driven by demand for labour from within and outside the EU. Lithuania, despite its small scale, doubled in number from 3,000 to 6,000 (+100.0%), mainly thanks to migrants from Belarus.

Table 6 shows the estimated numerical share of the most numerous nationalities of foreigners in the construction sector in the six Central European Countries in 2014 and 2023, referring to total employment (legal and illegal). Data for 2023 is based on official reports available for 2023 or 2022 (e.g., CSO "Foreigners performing work in Poland 2023" dated June 10, 2024, Destatis 2023, ČSÚ 2022/2023), with extrapolation to 2023 where full data has not yet been published.

Table 6. The most numerous nationalities of foreigners in the construction sector (2014 and 2023).

Country	Most numerous nationalities 2014	Estimated number 2014 (thousands)	Most numerous nationalities 2023	Estimated number 2023 (thousands)
Poland	1. Ukraine	40	1. Ukraine	105
	2. Belarus	3	2. Belarus	12
	3. Lithuania	2	3. Georgia	4
	4. Russia	1	4. India	2
Czech Republic	1. Ukraine	15	1. Ukraine	28
	2. Slovakia	3	2. Vietnam	4
	3. Poland	1	3. Poland	3
	4. Hungary	1	4. Romania	2
Slovakia	1. Ukraine	5	1. Ukraine	9
	2. Czech Republic	1	2. Romania	2
	3. Hungary	1	3. Serbia	1
	4. Poland	0.5	4. Czech Republic	1
Hungary	1. Ukraine	4	1. Ukraine	7
	2. Romania	1	2. Romania	3
	3. Slovakia	0.5	3. Serbia	1
	4. Serbia	0.5	4. China	1
Lithuania	1. Ukraine	2	1. Belarus	3
	2. Belarus	1	2. Ukraine	2
	3. Russia	0.5	3. Russia	1
	4. Latvia	0.5	4. Georgia	0.5
Germany	1. Poland	100	1. Poland	145
	2. Turkey	50	2. Romania	75
	3. Romania	20	3. Turkey	55
	4. Croatia	10	4. Ukraine	35

Source: Central Statistical Office (2024d); Polish Border Guard (2023); EURES (2023); Statistical Office of Slovakia (2023b); Hungarian Statistical Office (2023b); Eurostat (2024d); Bundesagentur für Arbeit (2023); International Labour Organization ILO (2023a).

In Poland, Ukrainians (40 thousand), Belarusians (3 thousand), Lithuanians (2 thousand) and Russians (1 thousand) predominated in 2014, with Ukrainians rising to 105 thousand in 2023, Belarusians to 12 thousand, with Georgians (4 thousand) and Indians (2 thousand) as new groups. In the Czech Republic, Ukrainians (15,000 in 2014, 28,000 in 2023) dominate, with Slovaks, Poles and Hungarians in 2014, and Vietnamese (4,000), Poles and Romanians in 2023. Slovakia had Ukrainians (5,000), Czechs, Hungarians and Poles in 2014, and Ukrainians (9,000), Romanians, Serbs and Czechs in 2023. In Hungary, Ukrainians (4,000 to 7,000) and Romanians (1,000 to 3,000) are the most numerous, with Slovaks and Serbs in 2014 and Serbs and Chinese in 2023. Germany employed Poles (100,000), Turks (50,000), Romanians and Croats in 2014, and Poles (145,000), Romanians (75,000), Turks and Ukrainians in 2023. In Lithuania, Ukrainians (2,000) and Belarusians (1,000) predominated in 2014, with Russians and Latvians, and in 2023 Belarusians (3,000), Ukrainians (2,000), Russians and Georgians.

The role of migrants in the construction sector in Central Europe is not limited to their direct contribution to employment in the industry but must be considered in the broader context of overall migration flows to the countries analysed. With the increasing influx of migrants, especially after 2014, triggered by factors such as EU enlargement, the war in Ukraine from 2022 and the migration policies of individual countries, the construction sector has become one of the main beneficiaries of this labour mobility. To better understand the importance of migrants in the construction industry, it is crucial to compare their numbers in the industry with the total number of migrants arriving in a country. Table 7 presents these figures for Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany in 2014 and 2024, showing how the concentration of migrants in the construction sector has changed against the background of overall migration trends. This analysis allows us to assess the extent to which construction attracts migrants compared to other sectors of the economy, and how migration policies and labour market needs shape these proportions.

Table 7. Number of migrants employed in the construction sector relative to all migrant arrivals in selected Central European Countries (2014-2024).

Country	Number of total migrants 2014 (thousands)	Number of migrants in construction 2014 (thousands)	Number of total migrants 2024 (thousands, estimated)	Number of migrants in construction 2024 (thousands, estimated)	Dynamics of change in share 2014-2024 (% pts)
Poland	220	47 (21.4%)	650	140 (21.5%)	+0.1
Czech Republic	80	20 (25.0%)	180	42 (23.3%)	-1.7
Slovakia	35	7 (20.0%)	70	15 (21.4%)	+1.4
Hungary	50	6 (12.0%)	90	13 (14.4%)	+2.4
Lithuania	20	3 (15.0%)	40	6 (15.0%)	0.0
Germany	1500	278 (18.5%)	2200	504 (22.9%)	+4.4

Source: Central Statistical Office (2024b); Czech Statistical Office (2023a); Statistical Office of Slovakia (2023c); Hungarian Statistical Office (2023c); Statistics Lithuania (2023a); Destatis (2024c); Eurostat (2024c); International Organization for Migration IOM (2023d).

Table 8 illustrates the number of migrants employed in the construction sector in relation to the total number of migrants arriving in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany in 2014 and 2024, along with the percentage and dynamics of change in this share.

Table 8. Impact of migration policies on migrant employment in the construction sector (2014-2024).

Country	Key migration policy (year of introduction)	Migrants in construction before change (thousands) (year)	Year	Migrants in construction after the change (thousands) (year)	Growth (%)
Poland	Simplification of procedures for Ukrainians (2017)	50 (2016)	2016	128 (2024)	+156%
Czech Republic	Program "Režim Ukrajina" (2022).	30 (2021)	2021	42 (2024)	+40%
Slovakia	Facilitation for EU migrants (2014)	7 (2014)	2014	15 (2024)	+114%
Hungary	Restrictions for non-EU migrants (2015)	6 (2014)	2014	13 (2024)	+117%
Lithuania	Simplifications for Belarusians (2020)	4 (2019)	2019	6 (2024)	+50%
Germany	Fachkräfteeinwanderungsges etz (2020)	350 (2019)	2019	484 (2024)	+38%

Source: Central Statistical Office (2024b); Czech Statistical Office (2023a); Statistical Office of Slovakia (2023c); Hungarian Statistical Office (2023c); Statistics Lithuania (2023b); Destatis (2024c); Eurostat (2024d); International Organization for Migration IOM (2023c).

In Poland, in 2014, 47,000 migrants worked in construction with a total of 220,000 migrant arrivals (21.4%), and in 2024, this number increased to 140,000 with 650,000 migrants (21.5%), indicating a stable, although slightly increasing (+0.1 percentage points) share of construction in migrant employment, mainly from Ukraine. In the Czech Republic, the share of migrants in construction fell from 25.0% (20,000 of 80,000) in 2014 to 23.3% (42,000 of 180,000) in 2024 (-1.7 percentage points), which may reflect the diversification of migrant employment in other sectors. Slovakia saw an increase from 20.0% (7,000 of 35,000) to 21.4% (15,000 of 70,000) (+1.4 percentage points), suggesting the growing importance of construction to migrants. Hungary increased its share from 12.0% (6 thousand from 50 thousand) to 14.4% (13 thousand from 90 thousand) (+2.4 percentage points), indicating the gradual attraction of migrants to the sector. Lithuania maintained a stable share of 15.0% (3 thousand from 20 thousand in 2014 and 6 thousand from 40 thousand in 2024), with no change in dynamics. Germany recorded the largest increase in share, from 18.5% (278 thousand from 1,500 thousand) in 2014 to 22.9% (504 thousand from 2,200 thousand) in 2024 (+4.4 percentage points), driven by strong demand for construction labour, especially from EU countries and Ukraine.

Migration policy plays a key role in shaping the availability of foreign labour in the construction sector, especially in the face of shortages of local workers and growing infrastructure needs in Central Europe. The introduction of visa facilitation, work permits, or integration programs has had varying effects on the inflow of migrants to the construction industry in the countries analysed between 2014 and 2024. Table 8 shows how selected migration policy changes in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany have affected the number of migrants employed in the construction sector, allowing an assessment of the effectiveness of these regulations in response to current challenges, such as the war in Ukraine and the Green Deal. This analysis provides data relevant to the design of future migration and integration strategies, which is one of the goals of the study.

Table 8 shows the impact of key changes in migration policy on migrant employment in the construction sector in six Central European Countries. In Poland, the simplification of visa procedures for Ukrainians in 2017 increased the number of migrants in construction from 50,000 in 2016 to 128,000 in 2024 (+156%), reflecting the construction boom and the influx of refugees after 2022. In the Czech Republic, the 2022 "Režim Ukrajina" program raised the number from 30,000 in 2021 to 42,000 in 2024 (+40%), supporting the sector after the war in Ukraine. Slovakia, with its facilitation of EU migrants since 2014, saw an increase from 7,000 to 15,000 (+114%). Hungary, despite 2015 restrictions, saw growth from 6,000 to 13,000 (+117%), thanks mainly to migrants from Ukraine and Romania. Lithuania, after facilitating Belarusians in 2020, increased from 4,000 to 6,000 (+50%). Germany, thanks to the 2020 skilled immigration law, saw an increase from 350,000 to 484,000 (+38%), attracting specialists. The data shows that liberal policies (Poland, Slovakia) have yielded more growth than restrictive ones (Hungary), although all countries have benefited from migrants in response to sector needs.

The transformation of the construction sector in Central Europe, driven by infrastructure investment and the requirements of the European Green Deal, requires migrants not only to be present, but also to adapt their skills to new market needs. Table 9 analyses the structure of migrant construction employment in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany in 2014 and 2024, dividing them into unskilled (e.g., labourers), skilled (e.g., masons, carpenters) and specialists (e.g., engineers, RES technicians). Changes in this structure reflect both the historical role of migrants as low-cost labour and their growing contribution to more advanced projects, which is key to understanding their impact on the future of the sector in the context of the Green Deal and current challenges.

Table 9 shows the evolution of the structure of migrant employment in the construction sector by skill level. In Poland, unskilled labourers accounted for 75% of migrants in 2014, but by 2024 their share had fallen to 60% (-15 percentage points), while skilled increased from 20% to 30% (+10 percentage points) and specialists from 5% to 10% (+5 percentage points), reflecting the demand for skills in Green Deal projects.

Table 9. Employment structure of migrants in the construction sector by qualification (2014-2024).

Country	Category	Share 2014 (%)	Share 2024 (%)	Change (% points)	Country	Category	Share 2014 (%)	Share 2024 (%)	Change (% points)
Poland	Unskilled	75	60	-15	Hungary	Unskilled	80	70	-10
	Qualified	20	30	+10		Qualified	15	20	+5
	Specialists	5	10	+5		Specialists	5	10	+5
Czech Republic	Unskilled	65	55	-10	Lithuania	Unskilled	70	65	-5
	Qualified	30	35	+5		Qualified	25	25	0
	Specialists	5	10	+5		Specialists	5	10	+5
Slovakia	Unskilled	70	60	-10	Germany	Unskilled	50	40	-10
	Qualified	25	30	+5		Qualified	30	35	+5
	Specialists	5	10	+5		Specialists	20	25	+5

Source: Eurostat (2024b); Central Statistical Office (2024d); Destatis (2024b); Spectis (2024c); International Labour Organization ILO (2023b).

In the Czech Republic and Slovakia, a similar trend: a decline in the unskilled (from 65% to 55% and from 70% to 60%) in favour of the skilled and specialists (+5-10 percentage points each). Hungary maintains a high share of unskilled (70% in 2024), but specialists have increased from 5% to 10%. Lithuania shows the least change, with unskilled at 65% in 2024, but specialists increased to 10%. Germany, with a more advanced market, has reduced the share of unskilled from 50% to 40%, increasing specialists from 20% to 25%. The trend indicates a gradual shift of migrants toward higher qualifications, supporting the transformation of the sector, although the unskilled still dominate in most countries.

The future role of migrants in the construction sector in Central Europe depends on the continuation of migration trends, EU policies (e.g., the Green Deal), as well as demographic and economic changes. Table 10 shows a forecast of migrant employment in construction in 2024-2030, based on extrapolation of current data (Tables 4, 5, 7) and assumptions about the stabilization of migrant inflows (e.g., Ukrainians after the war), the increase in demand for RES specialists and the impact of automation. This forecast provides a glimpse into the long-term implications of the role of migrants, which is important for understanding their impact on the region's future, according to the study's objective.

Table 10. Forecast of migrant employment trends in the construction sector (2024-2030).

Country	Migrants in construction 2024 (thousands)	Forecast 2030 (thousands)	Change 2024-2030 (%)	Key forecast factors
Poland	140	160	14	Stabilizing migration from Ukraine, Green Deal
Czech Republic	42	50	19	Increase in demand for RES, migration from Asia
Slovakia	15	18	20	EU investment, regional migration
Hungary	13	15	15	Migration restrictions, local projects
Lithuania	6	7	17	Migration from Belarus, stable demand
Germany	504	550	9	Automation, EU and non-EU specialists

Source: Author's elaboration based on European Commission (2023a); Organisation for Economic Co-operation and Development (2022); Spectis (2024b).

Table 10 forecasts the growth of migrant employment in the construction industry through 2030. In Poland, the number will increase from 140,000 in 2024 to 160,000 (+14%), driven by stabilizing migration from Ukraine and Green Deal projects, although the pace will slow due to market saturation. The Czech Republic will increase from 42,000 to 50,000 (+19%), driven by demand for RES specialists and migration from Asia. Slovakia will reach 18k (+20%) due to EU investment, and Hungary will reach 15k (+15%) despite restrictions. Lithuania will grow to 7 thousand (+17%), thanks mainly to Belarusians. Germany, from 504k to 550k (+9%), will see slower growth due to automation, but demand for specialists will remain. The forecast suggests a continuation of the role of migrants as a pillar of the sector, with increasing importance of qualifications and regional differences.

Conclusions

The survey provided a comprehensive picture of the impact of migrants on the construction sector in Poland, the Czech Republic, Slovakia, Hungary, Lithuania and Germany. The results confirm that foreign workers have become an indispensable pillar of the sector, filling labour gaps resulting from local labour shortages, aging populations and emigration to the West. The main objective of the study - to identify and compare the impact of foreign workers on employment in the construction sector between 2014 and 2024, in order to provide data for migration and integration policies in the face of contemporary challenges - was fully realized. The analysis not only revealed key trends and regional differences, but also answered the research questions, offering practical conclusions and forecasts for the future.

The first research question ("How have foreign migrants affected the dynamics of construction employment in Central Europe between 2014 and 2024?") showed a significant increase in the number of migrants in the sector. In Poland, their number in total employment increased by 150% (from 47,000 to 140,000), driven by the infrastructure boom and the influx of Ukrainians after 2022. In the Czech Republic, the increase was 87.5% (from 20,000 to 42,000), and in Germany 66.7% (from 278,000 to 504,000), reflecting the growing demand for labour in the face of EU funds and the Green Deal. The second question ("What are the differences in the role and impact of migrants between countries in the region in the context of current events?") revealed variation: Poland and the Czech Republic benefited from a "supply shock" from Ukraine (Kamyshnykova, 2023), Slovakia and Hungary experienced smaller but stable growth (+100% and +100%, respectively), Lithuania had the lowest dynamics (+100%, but from a small base of 3,000 to 6,000) due to emigration, and Germany attracted both unskilled and specialists from the EU. The third question ("What policies and social strategies can increase the contribution of migrants to the construction sector in the face of contemporary challenges?") was answered in the analysis of migration policies (Table 8): the liberal approach of Poland (+156% after 2017) and Slovakia (+114% after 2014) yielded greater benefits than the restrictive one of Hungary (+117% despite 2015 restrictions), suggesting the need for administrative and integration facilitation.

The results also indicate that the structure of migrant employment has evolved (Table 9). In Poland, the share of the unskilled fell from 75% to 60%, while the share of specialists rose from 5% to 10%, reflecting the demand for skills in sustainable construction. Similar trends are evident in the Czech Republic, Slovakia and Germany, although Hungary and Lithuania remain more dependent on unskilled labour. Projections for 2024-2030 (Table 10) suggest a further increase in the role of migrants, such as in Poland to 160,000 (+14%) and Germany to 550,000 (+9%), driven by stabilizing migration and the demands of the Green Deal.

Recommendations. Simplifying migration procedures: Countries should continue liberalizing visa policies and work permits, following the example of Poland (2017 simplifications for Ukrainians) or the Czech Republic ("Režim Ukrajina" of 2022) to increase the availability of migrants, especially from Ukraine, Belarus and Asia.

Investment in training: Programs to upgrade the skills of migrants, especially in renewable energy technologies (RES) and sustainable construction, can accelerate the sector's transformation, as changes in employment patterns show (Table 9).

Legalization and control of the shadow economy: The increase in illegal employment (e.g., in Poland from 6.4% to 8.9%, in Slovakia from 3.8% to 6.9%) requires more effective regulation, PIP inspections and incentives for legal work to improve the conditions of migrants and the stability of the sector.

Social integration: Creating integration programs, including language and housing support, can reduce ethnic enclaves and increase the long-term contribution of migrants, which is key to the challenges identified by Hack-Polay (2020).

The work stands out for its comprehensive comparative analysis of six countries, integration of statistical data (Tables 1-9) with forecasts (Table 10) and practical recommendations. Its uniqueness lies in capturing the evolving role of migrants - from cheap labour to skilled professionals - in the context of the Green Deal, the pandemic and the war in Ukraine. It provides not only data, but also strategies for policymakers, making it a valuable contribution to the migration and construction literature.

Further research should focus on several areas. First, analysing the impact of automation on migrant employment, especially in Germany, where it is projected to increase (Table 10), can clarify how technology will change labour demand. Second, the long-term effects of migrant integration, including their career advancement and impact on local communities, need to be deepened, especially in countries with a high proportion of enclaves (Favell, 2019). Third, increasing migration from Asia (e.g., India in Poland, Vietnam in the Czech Republic) deserves detailed study in the context of future sector needs. Finally, the impact of climate change on migration and construction - e.g., the need for disaster-resistant infrastructure - can open up a new dimension of analysis, linking ecology to the labour market.

The study provides a solid foundation for understanding the role of migrants in Construction sector in Central European Countries, offering both a retrospective and a forward-looking perspective. Its findings and recommendations can support policies that strengthen the region's economic resilience in the face of global challenges.

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The Influence of a Deficit in Employees' Dynamic Capabilities on Job Performance in Organisations During the Decline Stage of the Organisational Life Cycle as a Symptom of Organisational Death

Agnieszka Bienkowska [1], Katarzyna Tworek [2, *]

[1] Wroclaw University of Science and Technology, Poland
ORCID: 0000-0002-7498-6322
e-mail: agnieszka.bienkowska@pwr.edu.pl

[2] Wroclaw University of Science and Technology, Poland
ORCID: 0000-0002-6276-2436
e-mail: katarzyna.tworek@pwr.edu.pl

[*] Corresponding author: Katarzyna Tworek, katarzyna.tworek@pwr.edu.pl

Abstract

This article investigates the impact of employees' dynamic capabilities (EDCs) on job performance within organisations during the decline stage of the organisational life cycle (OLC), particularly as they approach organisational death. EDCs, which include an employee's ability to adapt, innovate, and solve problems, have been extensively studied in thriving organisations, but their role during organisational decline remains underexplored. This study addresses this gap by examining whether EDCs positively influence job performance through mediators such as work motivation, job satisfaction, and work engagement in organisations nearing the end of their operations. For two-part empirical analysis, data were gathered from organisations in Italy, Poland, and the USA, some of which were at varying stages of decline due to the external crisis caused by the COVID-19 pandemic. The results indicate that in organisations continuing operations, EDCs had a significant positive impact on job performance, mediated by work engagement, work motivation, and job satisfaction. However, in organisations heading toward death, EDCs failed to influence job performance significantly. The study concludes that EDCs' lack of impact on job performance may be a critical symptom of organisational death, suggesting that organisations unable to leverage their employees' capabilities during times of crisis may be doomed to failure. This research contributes to the OLC literature by identifying the absence of EDCs' influence on job performance as a key predictor of organisational demise, offering new insights for management practices during the decline phase of an organisation.

Key words

organisational death, employees' dynamic capabilities, job performance, organisational life cycle.

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Introduction

The subject of the organisational life cycle (OLC) has been the subject of scientific debate for a long time. Many authors who personalise organisation (by analogy with living organisms) point to the main stages of the organisational life cycle, which are, in simple terms, birth, development, maturity, and decline and/or death (Chandler, 1962; Quinn & Cameron, 1983; Mintzberg, 1989; Greiner, 1972; Hanks, 1990). Lester et al. (2023) underline that decline and death stages are not present in all OLC models. However, while the decline stage should be included in these models, it can be agreed that the death stage of the organisation – which can be seen as no longer belonging to the life of the organisation – goes beyond the OLC models, but accompanies them, as a closure of the organisation's functioning. In the approach considered in this article, both the organisational decline and the eventual death – which occurs because of this decline – of organisations will be treated as natural, albeit avoidable, stages in the life cycle of an organisation. The causes of their occurrence are most often connected to the environment (not necessarily only those perceived a priori as negative), which managers are unable or unwilling to cope with, thus triggering an escalation of negative phenomena in the organisation, including among employees, which subsequently result in the inability to achieve the organisation's goals in both the long and short term. It is not without reason that the concept of organisational decline "is characterised by politics and power (Mintzberg, 1984), as organisational members become more concerned with personal goals than they are with organisational goals" (Lester et al., 2023, p. 343) and "refers to deterioration in the capacity of a certain organisation to adapt to the environment within which it is embedded" (Mouzelis, 2017). In this context, it is natural to ask about the role of the dynamic capabilities of organisations, and particularly the dynamic capabilities of employees, in the stage of organisational decline. The relevance of this topic is further supported by bankruptcy prediction models studied in the literature and applied in practice, as well as by the analysis of symptoms indicating the possibility of organisational decline and death. Among these, a significant role is played by factors related to the broad area of human resource management and the ability of both employees and organisations to adapt to changes in their environment.

According to Teece (1997, p. 516), organisational dynamic capabilities are "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments". Similarly, Eisenhardt and Martin (2000, p. 1107) underlined that organisational dynamic capabilities can be understood as "the firm's processes that use resources – specifically the processes to integrate, reconfigure, gain and release resources – to match and even create market change". Employees' dynamic capabilities (EDCs) concern employees in the organisation, underlining that they are also in constant motion, being prepared and ready for changes in the organisation and the environment. They also have the ability to solve problems occurring because of them. This is because EDCs determine the level of abilities "to be sensitive to changes in the environment, to adapt to changes in the environment, to proactively solve problems arising in the workplace (if they occur), and include innovations in the workplace as well as abilities for continuous personal development and learning" (Bieńkowska & Tworek, 2020). However, not only the level of EDCs is important, but also their effective influence on parameters such as job-related attitudes and then on outcome measures of the employees and the organisation as a whole.

The importance of EDCs to the functioning of contemporary organisations (especially their employees) has been characterised in a number of academic studies (Bieńkowska & Tworek, 2020; Bieńkowska, 2021; Luo & Tworek, 2022). The impact of EDCs on job-related attitudes (Bieńkowska & Tworek, 2020; Wali et al., 2023; Alwali, 2023), job performance (Bieńkowska & Tworek, 2020), and organisational performance, as well as organisational reliability (Bieńkowska et al., 2021, Wali et al., 2023; Keane et al., 2024; Wang et al., 2024) or innovation (Fallon-Byrne & Harney, 2017), has been empirically proven. It was further found that EDCs affect job performance in four stages of crisis: prodromal, acute, chronic, and resolution crisis, with a significant role of person–job fit, work motivation, job satisfaction, and work engagement in boosting such relations (Tworek et al., 2023). Hence, EDCs play a significant role in organisational performance, including under conditions of organisational crisis (Bieńkowska et al., 2021).

Therefore, the question arises of how EDCs behave among organisations in a stage of decline, moving towards the end of their activity, and how the mechanism of EDCs impacts on the job performance of employees at this stage. There is a research gap in this area in management science. It can be assumed that the potential of employees, lying in their dynamic capabilities, does not impact job performance and other organisational results in a negative way. However, the lack of positive impact of EDCs on job performance implies a lack of utilisation of employees' capital, especially in a dynamically changing environment when change is necessary. This may be a direct contributor to the ultimate death of the organisation.

In this context, the aim of this study is to verify the EDC-based model of job performance for organizations that are in the stage of decline (moving toward organizational death), and to compare it with the model for organizations that were in various other stages of OLC. They were therefore operating without any threat to their existence. The present study will therefore be a probe to complement the state of knowledge concerning EDCs in management sciences in the area of symptoms of organizational decline and death or models of bankruptcy prediction (Altman, 1968; Holda, 2001). The phenomenon of lack of influence of EDCs on job performance should be particularly evident in a crisis environment, where the organisation faces the challenges of making decisions and operating in a high-risk, uncertain and time-critical environment.

In order to achieve the aim, the critical literature analysis was performed, and the hypothesis was then empirically verified using two different data sets. The first empirical research, conducted in one point in time among organizations from Italy, USA and Poland, in which the information about the end of life of the organization is obtained based on the declaration of the respondent. The second empirical research, conducted on the same sample of organizations operating in Italy in three points in time, in which the information about the end of life of the organization is obtained from its confirmed death. Both were compared with organizations, which declared (in the first research) or shown (in the second research) their ability to continue operations. It should also be mentioned that both studies were carried out under the conditions of an external crisis caused by a Black Swan-type phenomenon (Taleb, 2007) – i.e. during the COVID-19 pandemic, which fundamentally affected the operating conditions of the organization, i.e. the dynamics, complexity, and unpredictability of changes in the environment. All of these naturally triggered crises in organizations increased the likelihood of their death, forcing organizations to make immediate adaptive or pre-emptive changes. Not all organizations have been successful, and this has caused them to enter a stage of decline, which ended with their death, which is the focus of this study.

1. Literature Review

1.1 Decline and death of organizations as stages accompanying organizational life cycles

The life cycle of an organization is defined as the succession of its previous states, indicating specific differences, stimulated by a variety of internal and external forces (Machaczka 1998). OLC theories are widely used and quite schematic (Mintzberg, 1989; Lippitt & Schmidt, 1967; Greiner, 1972; Hanks, 1990; Chandler, 1962; Lester et al., 2023). Specific stages of the OLC are usually distinguished, among which three base stages appear in almost every model: birth, youth and maturity (after Lippitt & Schmidt, 1967). In various developed models, there are also other stages given. For example, Quinn and Cameron (1983) indicate the stage of entrepreneurship, collectivity, formalization and control, and creation and adjustment of structure. In some models, the decline and/or death of the organization appear (Mintzberg 1989; Miller & Friesen 1984; Adizes 1979) treated as one or two separate stages. It is interesting to note that they do not appear in all OLC models, even though the decline stage should be clearly understood one of the stages of OLC models.

However, it seems that organizational death is in itself the opposite of life, and as such it is clear that this stage is not included in OLC models. This does not change the fact that the death stage should close the life of any organization and in this context, it accompanies OLC models immanently. Perhaps one should speak of organizational life and/or death cycle models. Moreover, it is clear that OLC theories describe specific sets of criteria that allow to assess the degree of identification with a particular stage of development, thus providing an indication for reaching the next stage or warning of emerging difficulties. There is a consensus among researchers on the validity of incorporating the assumptions of these theories into both management science and practice (Mosca et al., 2021; Tam & Gray, 2016).

Considering the decline stage of OLC itself, it should be noted that modern organizations are formed, grow and develop in an environment characterized by high complexity and high dynamics – usually known as VUCA, or more recently even BANI (Troise et al., 2022). The events occurring in the environment are also difficult to predict, so the organizations also operate under conditions of high uncertainty and even under conditions that are by definition impossible to predict (for example, the Black Swan-type phenomena noted in recent times (Taleb, 2007). Growing adversity of external environment is a common reason for the organization to enter decline stage (Miller & Friesen, 1984). The decline stage in an organization is characterized by certain negative trends within the organization, which exacerbate problems in the organization's environment. These include, for example, a centralized structure with few control systems, not particularly sophisticated information processing (however, usually, badly needed), centralized decision making (not complex) or leaving decisions in hands of a few conservative managers (Lester et al., 2003). The indicated organizational operating conditions (internal and external) enable the occurrence of intra-organizational crises, following which the probability of lack of continuity or even organizational death increases. Especially if this is accompanied by the phenomenon of growing internal rigidity (Adizes, 1979). "For some organizations, the inability to meet the external demands of a former stage has led them to a period of decline where they experience a lack of profit and a loss of market share (Miller & Friesen, 1984)" (Lester et al., 2023, p. 343). In this context, the question arises as to how the EDCs (being the negation of organizational rigidity) influence the job performance of employees in such organizations. It is the factor, which influence is crucial for reversing the course into organizational death, as the absence of this influence may mean a lack of utilization of employees' capital especially in a dynamically changing environment, when change is necessary.

1.2 Lack of EDCs impact on job performance, organizational decline and death

Both in the literature and in management practice, there is a a lot of attention concerning both predictive models of bankruptcy and symptoms that indicate the possibility of organizational decline or death. The former - as part of bankruptcy theory (Schwartz, 2004) - focuses in particular on hard evidence from the area of financial parameters and is based on statistical discriminant analysis (Altman, 1968; Holda, 2001), such as – in simple terms – working capital, financial result or sales revenue. These are early warning models for business risks. The later refers to exogenous and endogenous (Holda & Strojny, 2019) causes of bankruptcy, often defined qualitatively (Rogowski, 2015). Examples of endogenous factors are the inability of organization to adapt to the changing economic environment or the inappropriate use of financial risk management instruments, thus referring to mismanagement (Szewc-Rogalska, 2014), which is in line with the statements of Slatter and Lovett (2001), who argue that virtually all causes of deteriorating organizational performance can be traced back to mismanagement. By skilfully identifying the causes, it is possible to isolate the symptoms of an organization's decline and death. The symptom is generally understood as a sign of a negative phenomenon. Symptoms not only indicate current issues but also serve as predictors of future outcomes, which is why they play a critical role in diagnosing the causes of organizational decline and in identifying strategies for bankruptcy prevention.

When analysing the causes of organizational death relating to the human resources management area, the literature highlights the importance of: lack of employee motivation (Santorelli, 2013; Kaczmarek, 2002; Swierk & Banach, 2013), poorly delegated competences, lack of employee development (Swierk & Banach, 2013), low qualifications of managers and executives (Tokarski, 2012; Prusak, 2001; Mączyńska, 2013), low adaptability to market changes (Mączyńska, 2013), or lack of commitment (Kaczmarek, 2002). In this context, it seems possible to turn towards the EDC-based model of job performance as a concept combining the above-mentioned elements and indicating their impact (or rather lack thereof) on employees' job performance.

In this context, the lack of influence of EDCs on job performance can be seen as a key symptom of organizational decline and death. EDCs, as the abilities of employees to adapt, innovate, and respond to change, are essential for sustaining job performance in an evolving environment. When these capabilities deteriorate, it signals deeper issues within the organization, forecasting future failure if unaddressed. The phenomenon of lack of influence of EDCs on job performance should be particularly evident in a crisis environment, where the organization faces the challenges of making decisions and operating in a high-risk, uncertain and time-critical environment.

Crises, however, can also serve as catalysts for transformation, pushing organizations to adapt to external changes. For this to happen, several steps must be taken: recognizing the crisis early, diagnosing its causes and symptoms, and focusing on solving the most strategic, long-term problems (Czerska, 1996). Failure to respond quickly and appropriately leads to missed opportunities and delayed actions. This often results in the organization's inability to implement necessary changes, despite recognizing the need (Weaven et al., 2021; Gupta et al, 2024). The life-cycle models of organizations underscore the importance of constant adaptation to an evolving landscape. However, when an organization fails to leverage the dynamic capabilities of its workforce, it becomes trapped in a state of stagnation and eventual decline, which may ultimately lead to its death.

The lack of employees' dynamic capabilities positive influence on job performance can potentially lead to such organizational death (Weaven et al., 2021; Gupta et al, 2024). This issue may be compounded by the perspectives of work motivation, job satisfaction, and work engagement, crucial for EDC-based job performance model (Bieńkowska & Tworek, 2021), critical for maintaining high levels of job performance in any organization.

Organizational death usually starts with some crisis and inability to tackle these challenges by the organization. Employees may feel overwhelmed by the challenges posed by rapidly changing environment. This can lead to a decline in work motivation, as employees may perceive their inability to adapt as a personal failure. When motivation wanes, it cannot remain a bridge between a proper use of EDCs and their job performance, which typically suffers, as employees may disengage from their tasks and responsibilities (Teece et al., 1997; Amankwah-Amoah et al., 2021).

Moreover, the inability to effectively respond to challenges can lead to frustration and dissatisfaction among employees. When employees feel they lack the skills or support to navigate their roles successfully, their overall job satisfaction diminishes (Weaven et al., 2021), deteriorating the influence of EDCs on job performance through job satisfaction. This dissatisfaction can result in higher turnover rates and a lack of commitment to the organization, further destabilizing the workforce and impacting job performance, as EDCs cannot be properly used in such environment (Cortez & Johnston, 2020; Amankwah-Amoah et al., 2022). The inability to effectively utilize dynamic capabilities can further lead to frustration and loss of satisfaction among employees. When employees are unable to engage in meaningful work or see the impact of their contributions, their job satisfaction declines (Smallbone et al., 2012; Weaven et al., 2021).

Dynamic capabilities are essential for fostering employees' engagement, particularly in times of crisis (Gupta et al, 2024). Employees who feel equipped to handle challenges are more likely to be engaged in their work. Conversely, when employees lack the ability to tackle challenges even with their EDCs, their engagement levels drop, leading to a lack of initiative and creativity in problem-solving and mitigating engagement as the bridge between EDCs and job performance. This disengagement can hinder innovation and responsiveness, which are vital for organizational survival due to lack of positive influence of their EDCs on job performance (Amankwah-Amoah et al., 2021; Teece, 2007). That is because work engagement is closely tied to an employee's ability to leverage their skills and capabilities effectively. Employees who feel disconnected from their work and the organization's goals lead to a lack of initiative and a passive approach to problem-solving, which does not allow for positive impact of EDCs on job performance (Cegarra-Leiva et al., 2012; Weaven et al., 2021).

Moreover, the absence of collaborative decision-making capabilities can disrupt team dynamics, leading to poor communication and a lack of cohesion among team members. When employees do not engage effectively with one another, it can create a toxic work environment, further diminishing motivation and satisfaction (Cortez & Johnston, 2020). This breakdown in teamwork can lead to inefficiencies and errors, further impacting work motivation, job satisfaction and work engagement and further declining their ability to act as a bridge between EDCs and job performance, ultimately affecting organization (Cortez & Johnston, 2020; Amankwah-Amoah et al., 2021). Furthermore, when some team members struggle to adapt or innovate and put their EDCs in proper use, it can create frustration among more capable colleagues, leading to conflicts and a breakdown in collaboration. This can further diminish motivation and engagement across the team, resulting in a collective decline in job performance (Teece, 2012).

Finally, employees with limited possibility to meaningfully use their dynamic capabilities may struggle to identify and seize new opportunities for growth and improvement. This inability can lead to stagnation within the organization, as employees may not feel empowered to innovate or contribute to strategic initiatives. The lack of proactive behaviour can result in missed opportunities, which can be detrimental to the organization's long-term viability (Amankwah-Amoah et al., 2022; Teece et al., 1997).

However, among organizations already in crisis, employees lack of possibility to properly use their EDCs first and foremost hinder the organization recovery efforts, leading to long-term consequences, including potential death (Mahto et al., 2022). It is supported by view in various contemporary literature sources. Doern et al. (2019) emphasize that during economic downturns, the ability of employees to utilize their skills and capabilities is crucial for survival. A lack of effective use of these capabilities can hinder recovery efforts and lead to organizational decline. Cegarra-Leiva et al. (2012) highlight that organizations that fail to harness their employees' dynamic capabilities during crises may face significant challenges in recovery, which can ultimately threaten their long-term viability. It remains in line with authors contributing to the development of dynamic capabilities perspective, as Winter (2003) notes that understanding and effectively deploying dynamic capabilities is critical for organizations facing crises. A failure to do so can result in missed opportunities for recovery and adaptation, leading to long-term detrimental effects.

Therefore, it seems that the following hypothesis may be proposed:

H: EDCs are not influencing job performance through work motivation, job satisfaction and work engagement in organizations preceding their death.

2. Methodology

Two types of research were conducted in order to verify the hypotheses. The first one, conducted in one point in time among organizations from Italy, USA and Poland, in which the information about the end of life of the organization is obtained based on the declaration of the respondent. The second one, conducted on the same sample of organizations operating in Italy in three points in time, in which the information about the end of life of the organization is obtained from its confirmed death.

2.1 First research – sample and methodology

The study took place in February 2021, during the ongoing stage of the COVID-19 pandemic and was finances from NCN OPUS project 2020/37/B/HS4/00130 titled "Development of the Job Performance model based on EDC for various phases of crisis in organization". It was a point in time when many countries were experiencing a new wave of COVID-19, driven by emerging variants of the virus. This period was marked by fluctuating case numbers, the introduction of vaccination programs, and varying levels of restrictions across different regions, which was causing crisis to emerge in organizations and not all of them were able to maintain their continuity. It was conducted using the Computer-Assisted Web Interview (CAWI) method among managers of organizations. The sample consisted of 1197 organizations from Poland, Italy, and the USA. In order to verify the hypotheses, the sample will be divided into two groups: (1) organizations declaring ability to continue their operations and (2) organizations declaring lack of ability to continue their operations. Table 1 shows the division among them, showing how many organizations declared the ability to continue operations and how many organizations declared lack of ability to continue operations.

Table 1. Sample of organizations included in first research.

country	declared ability to continue operations					declared lack of ability to continue operations
	not in crisis	1st stage	2nd stage	3rd stage	4th stage	
Poland	81	75	124	121	25	27
USA	70	120	212	85	14	49
Italy	72	94	44	17	6	18
Total	223	338	377	127	38	94

Source: own work.

2.2 Second research – samples and methodology

Research was conducted in three stages, in order to verify the hypotheses concerning organizations, which died.

Stage 1: Early Pandemic – March 2020

The first stage of the study was conducted during the early stage of the COVID-19 pandemic, specifically in the week of March 18–22, 2020. This period marked the onset of the pandemic in Italy, where the country was grappling with an exponential rise in COVID-19 cases, surpassing 40,000, and a death toll exceeding 4,000. This was the initial wave of the pandemic, characterized by the sudden implementation of strict lockdown measures and the forced transition to remote work for many organizations. This stage aimed to assess how these organizations were adapting to the abrupt and severe changes, providing a unique opportunity to evaluate organizational resilience in a crisis. It was conducted using the Computer-Assisted Web Interview (CAWI) method among managers of organizations. The sample consisted of 115 organizations of varying sizes and operational durations:

- Micro (below 10 people): 19 organizations
- Small (11–50 people): 27 organizations
- Medium (51–250 people): 36 organizations
- Large (above 250 people): 33 organizations

The surveyed organizations included those that had been operational for less than a year to those with more than 10 years of operation, offering a broad perspective on how organizations at different stages of development responded to the crisis during the early stage of the pandemic.

Stage 2: Post-Initial Wave – October 2020

The second stage of the study took place in October 2020, following the initial wave of the COVID-19 pandemic and during a period where many countries, including Italy, were dealing with the aftermath of the first wave of the pandemic and preparing for potential subsequent waves. This stage involved a more extensive survey conducted in Italy, a time when organizations were adapting to a "new normal" with ongoing restrictions and a heightened awareness of the pandemic's long-term impact and provided insights into how organizations were navigating the continued challenges posed by the pandemic after the initial shock had subsided. It was conducted using the Computer-Assisted Web Interview (CAWI) method among managers of organizations.

The sample consisted of 378 organizations from Poland (not included in this study) and 115 same organizations from Italy. Out of 115 organization, 99 responded, and 16 were unable to respond because they stopped their operations between 1st and 2nd stage of the study.

Stage 3: Ongoing Pandemic – February 2021

The third stage of the study took place in February 2021, during the ongoing stage of the COVID-19 pandemic. By this time, many countries were experiencing a new wave of COVID-19, driven by emerging variants of the virus. This period was marked by fluctuating case numbers, the introduction of vaccination programs, and varying levels of restrictions across different regions. The study considered this period as a critical stage where organizations were dealing with prolonged crisis conditions and was focusing on how organizations were managing during this prolonged crisis period. It was conducted using the Computer-Assisted Web Interview (CAWI) method among managers of organizations.

The sample consisted of 1197 organizations from Poland (453), Italy (251), and the USA (550) (not all included in this study). Among them, the same 115 organizations from Italy were once again surveyed. Out of 115 organization, 91 responded, 16 which have not responded during 2nd stage have still remained un-operational, and additional 8 have not responded because they stopped their operations between 2nd and 3rd stage of the study.

Table 2. Size and time of operation of organizations included in the sample of second research.

Organization Size	Time of Operations				Total
	Less Than a Year	1 to 5 Years	5 to 10 Years	More Than 10 Years	
Micro (below 10 people)	6	5	4	4	19
Small (11–50 people)	4	15	7	1	27
Medium (51–250 people)	1	8	20	7	36
Large (above 250 people)	2	4	14	13	33
Total	13	32	45	25	115

Source: own work.

In order to verify the hypotheses, the sample will be divided into three groups: (1) organizations continuing their operations, (2) organizations, which stopped their operations between 1st and 2nd stage of study and (3) organizations, which stopped their operations between 2nd and 3rd stage of study.

2.3 Variables selection

The study utilized multiple variables, each measured using established scales to assess various aspects of employee attitudes and behaviours in each stage of the study. Below is a description of these variables and the corresponding measurement methods:

Employee Dynamic Capabilities were assessed through four dimensions: sensitivity to changes in the environment, ability to adapt to changes in the environment, ability to solve problems in the workplace (including innovation), and the ability for continuous personal development. These dimensions were measured using a 5-point Likert scale, allowing respondents to indicate the degree to which they agreed with statements related to these capabilities (Bieńkowska & Tworek, 2020).

Person-Job Fit was measured using a scale developed from the research of Saks and Ashforth (1997). The first stage scale consisted of one item and final scale consisted of three items, each using a 5-point Likert scale, assessing how well employees perceived their job to fit their personal attributes and skills.

Work Motivation was measured based on the conceptual framework provided by Hackman and Oldham (1974). The first stage scale consisted of one item and final scale consisted of three items, also using a 5-point Likert scale, designed to gauge the level of intrinsic motivation employees experienced in their roles.

Job Satisfaction was measured at a global level, without reference to specific facets of the job, following the approach of Judge, Boudreau, and Bretz (1994). This variable was assessed using a revised version of the Job Diagnostic Survey, which included one item during first stage scale and three items using a 5-point Likert scale in final scale, focusing on the overall satisfaction and general feelings towards the job.

Work Engagement was conceptualized based on the assumption that engaged employees feel an energetic and effective connection to their work, perceiving themselves as capable of meeting job demands (Schaufeli & Bakker, 2004). The scale in first stage consisted of one item and in final scale consisted of three items using a 5-point Likert scale.

Job Performance was assessed across four aspects: task proficiency, task meticulousness, work discipline, and work improvement & readiness for innovation. The scale, based on the works of Kwahk and Park (2018), included four items measured on a 5-point Likert scale, providing a comprehensive evaluation of employees' performance.

The detailed analysis of measurement scale, confirming their fit is given in Table 3 for the first research and in Table 4 for the second research, showing that alpha Cronbach remains within the optimal limits, and exploratory factor analysis shows that AVE values also remain high enough (additionally, all factor loadings remain above 0,7).

Table 3. Variables overview – first research.

Stage	Stage 2		
Variable	Items	CA	AVE
Satisfaction (Satisf)	3	0,630	0,576
Motivation (Motiv)	3	0,714	0,637
Work engagement (WrkEng)	3	0,714	0,636
Job performance (JobPerf)	4	0,753	0,577
Person – job fit (PJfit)	3	0,585	0,547
EDC (EDC)	8	0,843	0,478

Source: own work.

Table 4. Variables overview – second research.

Stage	Stage 1			Stage 2			Stage 3		
Variable	Items	CA	AVE	Items	CA	AVE	Items	CA	AVE
Satisfaction (Satisf)	1	--	--	3	0,630	0,576	3	0,594	0,711
Motivation (Motiv)	1	--	--	3	0,714	0,637	3	0,639	0,581
Work engagement (WrkEng)	1	--	--	3	0,714	0,636	3	0,666	0,599
Job performance (JobPerf)	4	0,909	0,677	4	0,753	0,577	4	0,812	0,474
Person – job fit (PJfit)	1	--	--	3	0,585	0,547	3	0,785	0,621
EDC (EDC)	4	0,853	0,563	8	0,843	0,478	8	0,821	0,543

Source: own work.

3. Research Results

3.1 First research – research results

Multigroup path analysis was performed using IBM SPSS AMOS and the well-fitted and statistically significant model was created. The fit of the model was measured. It was assessed with TLI and CFI (sufficient values above 0,8) and RMSEA (sufficient values below 0,2). The obtained model was statistically significant and well-fitted: Chi2 (91) = 953,663; p = 0,001; CFI = 0,836, TLI = 0,922; RMSEA = 0,088. Hence, it can be established that comparative fit index and Tucker-Lewis index are sufficient to form conclusions based on the obtained model and the RMSEA show a very good fit in the model, showing the more than satisfactory level of badness of the model. The overview of the regression weights established for obtained model for each group of organizations are presented in Tables 5 and 6.

Table 5. Regression weights for organizations declaring ability to continue operations.

Declared ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.644	0.041	15,642	<0.001
WrkEng	<---	PJfit	0.629	0.054	11,560	<0.001
Motiv	<---	PJfit	0.684	0.052	13,234	<0.001
Satisf	<---	PJfit	0.575	0.048	11,922	<0.001
JobPerf	<---	WrkEng	0.152	0.037	4,153	<0.001
JobPerf	<---	Motiv	0.230	0.037	6,179	<0.001
JobPerf	<---	Satisf	0,124	0.041	3,023	0.003

Note: S.E. – standard error, C.R. – critical ratio, p – probability ratio.
Source: own work.

Table 6. Regression weights for organizations declaring lack of ability to continue operations.

Declared lack of ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.850	0.133	6.405	<0.001
WrkEng	<---	PJfit	0.637	0.130	4.881	<0.001
Motiv	<---	PJfit	0.591	0.120	4.938	<0.001
Satisf	<---	PJfit	0.600	0.133	4.524	<0.001
JobPerf	<---	WrkEng	0.239	0.137	1.744	0.081
JobPerf	<---	Motiv	0.225	0.148	1.520	0.129
JobPerf	<---	Satisf	0.038	0.136	0.278	0.781

Note: S.E. – standard error, C.R. – critical ratio, p – probability ratio.
Source: own work.

The obtained results of first research, in which the continuity of operations (or lack of it) was a declaration, confirm the initial assumptions. Organizations continuing their operations clearly show that there is an influence of EDC on job performance, mediated by P-J fit, work engagement and work motivation. However, organizations, which were not continuing their operations show lack of such influence, as the relation between all variables and job performance within the model are not statistically significant. Hence, the results from first research allow to accept the proposed hypothesis: EDCs are not influencing job performance through work motivation, job satisfaction and work engagement in organizations preceding their death.

3.2 Second research – research results

In case of second research, two sets of multigroup path analysis were performed using IBM SPSS AMOS. First set for organizations in 2nd stage of research and second set for organizations in 3rd stage of research. For organizations in 2nd stage of research, the well-fitted and statistically significant model was created. The obtained model was statistically significant and well-fitted: Chi2 (8) = 33,034; p = 0,001; CFI = 0,926 (TLI = 0,930); RMSEA = 0,073. Hence, it can be established that comparative fit index, Tucker-Lewis index and RMSEA are sufficient to form conclusions based on the obtained model. The overview of the regression weights established for obtained model for each group of organizations (continuing operations in 2nd stage of research and discontinuing operations in 2nd stage of research) are presented in table 7 and 8.

Table 7. Regression weights for organizations continuing operations in 2nd stage.

Declared lack of ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.950	0.143	9.765	<0.001
WrkEng	<---	PJfit	0.630	0.098	6.457	<0.001
Motiv	<---	PJfit	0.613	0.053	11.543	<0.001
Satisf	<---	PJfit	0.622	0.059	10.503	<0.001
JobPerf	<---	WrkEng	0.220	0.086	2.562	0.01
JobPerf	<---	Motiv	0.543	0.136	3.983	<0.001
JobPerf	<---	Satisf	0.022	0.130	0.172	0.864

*S.E. – standard error, C.R. – critical ratio, p – probability ratio
Source: own work.

Table 8. Regression weights for organizations discontinuing operations in 2nd stage.

Declared ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.644	0.051	8.742	<0.001
WrkEng	<---	PJfit	0.765	0.099	7.715	<0.001
Motiv	<---	PJfit	0.717	0.051	14.096	<0.001
Satisf	<---	PJfit	0.801	0.047	16.918	<0.001
JobPerf	<---	WrkEng	0.549	0.540	1.016	0.309
JobPerf	<---	Motiv	0.636	0.930	0.684	0.494
JobPerf	<---	Satisf	1.446	0.854	1.692	0.091

Note: S.E. – standard error, C.R. – critical ratio, p – probability ratio.
Source: own work.

For organizations in 3rd stage of research, the well-fitted and statistically significant model was created. The obtained model was statistically significant and well-fitted: Chi2 (8) = 33,034; p = 0,001; CFI = 0,929 (TLI = 0,923); RMSEA = 0,108. Hence, it can be established that comparative fit index, Tucker-Lewis index and RMSEA are sufficient to form conclusions based on the obtained model. The overview of the regression weights established for obtained model for each group of organizations (continuing operations in 3rd stage of research and discontinuing operations in 3rd stage of research) are presented in table 9 and 10.

Table 9. Regression weights for organizations continuing operations in 3rd stage.

Declared lack of ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.933	0.076	9.607	<0.001
WrkEng	<---	PJfit	0.639	0.109	5.872	<0.001
Motiv	<---	PJfit	0.854	0.092	9.260	<0.001
Satisf	<---	PJfit	0.562	0.121	4.645	<0.001
JobPerf	<---	WrkEng	0.185	0.076	2.434	<0.001
JobPerf	<---	Motiv	0.472	0.077	6.114	<0.001
JobPerf	<---	Satisf	0.086	0.071	1.217	0,015

Note: S.E. – standard error, C.R. – critical ratio, p – probability ratio.
Source: own work.

Table 10. Regression weights for organizations discontinuing operations in 3rd stage.

Declared lack of ability to continue operations			Estimate	S.E.	C.R.	P
PJfit	<---	EDC	0.540	0.091	5.403	<0.001
WrkEng	<---	PJfit	0.685	0.456	1.502	0.133
Motiv	<---	PJfit	0.999	0.105	9.496	<0.001
Satisf	<---	PJfit	0.169	0.282	4.153	<0.001
JobPerf	<---	WrkEng	-0.014	0.191	-0.075	0.083
JobPerf	<---	Motiv	0.816	0.402	2.028	0.940
JobPerf	<---	Satisf	0.005	0.288	0.019	0.985

Note: S.E. – standard error, C.R. – critical ratio, p – probability ratio.
Source: own work.

Therefore, the obtained results of second research confirm the results obtained from first research. However, in this case, the continuity of operations (or lack of it) was not a declaration, but an observed fact. In case of organizations from 2nd stage of research, those continuing their operations clearly show that there is an influence of EDC on job performance, mediated by P-J fit, work engagement and work motivation. However, those organizations, which were not continuing their operations show lack of such influence, as the relation between all variables and job performance within the model are not statistically significant. Similar results are obtained for organizations from 3rd stage of research. Those continuing their operations clearly show that there is an influence of EDC on job performance, mediated by P-J fit, work engagement, work motivation and job satisfaction. Once again, those organizations, which were not continuing their operations show lack of such influence, as the relation between all variables and job performance within the model are not statistically significant. Hence, the results from second research also allow to accept the proposed hypothesis: EDCs are not influencing job performance through work motivation, job satisfaction and work engagement in organizations preceding their death.

4. Discussion

The proposed research provides significant insights into the EDCs role within the framework of the OLC literature, offering a new and fresh perspective on the decline and eventual death of organizations in the context of predictive models of bankruptcy and symptoms of organizational demise or death, among which a significant role is played by those related to the broader field of human resources management and the adaptation of employees and the organization to changes in the environment. While prior research has emphasized the importance of dynamic capabilities at the organizational level (Teece, 1997; Eisenhardt & Martin, 2000), this study highlights a critical gap in understanding the role of EDCs (as the dynamic capabilities of employees themselves, not organization as a whole) during the organization decline, aimed at its death, particularly in organizations facing existential threats. It was assumed that the crisis in which the organizations under study found themselves, being a Black Swan-type phenomenon (Taleb, 2007), allowing the phenomena under analysis to be precisely observed. The findings of this study make a notable contribution to the literature by identifying the lack of EDCs' influence on job performance as a critical indicator of organizational death.

Previous studies (Bieńkowska & Tworek, 2020) have shown that EDCs positively impact job performance by enhancing employees' adaptability, problem-solving capabilities, and innovation. However, this research demonstrates that when the influence of EDCs on job performance ceases to exist – specifically through the key mediators such as work motivation, job satisfaction, and work engagement – the organization is likely approaching its demise, and it may be one of the reasons for its death.

This was confirmed by the results of an empirical study in which, among organizations that declared their ability to continue in business, EDCs had a clear and statistically significant positive impact on job performance, mediated by variables such as work motivation, job satisfaction and work engagement. Conversely, in organizations that were unable to continue their operations or were in the final moments of decline, the relationship between EDCs and job performance was not statistically significant. This lack of impact highlights a critical failure to realize the potential of employees, reinforcing the view that when EDCs no longer contribute to performance outcomes, it signals an organization's inability to adapt and survive in a changing environment. Data from both empirical studies - those using self-reported operational capability and those using confirmed organizational death - strongly support the theoretical framework that the lack of impact of EDCs on performance outcomes is a reliable predictor of organizational death. The results support this study's contribution to the OLC literature by empirically demonstrating that the lack of EDC use during organizational demise is a critical symptom of impending organizational death.

The absence of EDCs' impact signifies not merely a low level of dynamic capabilities but, more critically, a disconnect between employees' abilities and the organizational outcomes needed for its survival, showing lack of ability to properly use employees as the main resource of the organization. This disconnect, as the results suggest, is a symptom of deeper organizational stagnation that often precedes organizational death. This challenges the traditional view that organizations can rely solely on organizational dynamic capabilities to adapt to environmental changes (Salvato & Vassolo, 2018), emphasizing that the mere presence of EDCs is insufficient if they do not translate into tangible performance outcomes.

Moreover, the study extends the OLC literature by positioning the lack of EDCs influence on job performance as a critical symptom of organizational death, which complements existing models of organizational decline (Mintzberg, 1989; Miller & Friesen, 1984; Mosca et al., 2021). While decline has long been recognized as a stage of OLC, the findings suggest that the absence of EDCs' influence on job performance serves as an early warning signal that organizations are failing to harness their most valuable asset – employees' capabilities. In environments characterized by volatility and uncertainty, organizations that cannot leverage EDCs to maintain performance are likely to face imminent failure.

Hence, this research significantly contributes to the literature by framing the lack of EDCs' influence on job performance as a leading indicator of organizational death. It provides a valuable lens for understanding how organizations in decline fail to utilize their employees' dynamic capabilities, which ultimately accelerates their collapse. Future research can build on this study by exploring interventions that could restore the influence of EDCs in declining organizations, potentially offering pathways for recovery and organizational renewal.

Conclusions

This study makes a significant contribution to the OLC literature by identifying the lack of EDCs influence on job performance as a critical indicator of organizational death. It extends existing research by empirically demonstrating that when EDCs fail to impact job performance during the decline stage, it signals a deeper organizational inability to adapt, ultimately leading to failure. This study adds to the understanding of EDCs' role not only in organizational survival but also in predicting the end of an organization's life cycle, offering a new lens for analysing organizational decline.

While this study provides valuable insights into the relationship between EDCs and organizational decline, several limitations should be acknowledged. First, the research primarily focuses on organizations from three countries (Italy, Poland, and the USA) and during a specific external crisis (the COVID-19 pandemic). As such, the findings may not be fully generalizable to organizations operating in different cultural contexts or under different external pressures. Second, the study relies on self-reported data for the first stage of research, which may introduce bias due to respondents' subjective views on their organization's ability to survive. The second stage of research, though more objective, still does not capture real-time organizational behaviours, as it was conducted at set intervals. This may limit the ability to observe rapid changes in EDCs utilization or the exact moment an organization moves from decline to death.

Future research should aim to address these limitations by broadening the scope to a more diverse set of organizations, both geographically and by industry. Comparative studies in different cultural and economic settings would help to verify the results and assess whether the relationship between EDCs and organizational death persists in different contexts. In addition, longitudinal studies involving real-time data on organizational decline and death could provide deeper insights into the dynamics of EDC over time and how organizations attempt to reverse the decline stage.

Further research could also explore the role of external variables, such as leadership effectiveness, market competition or technological innovation, as moderators in the relationship between EDC and organizational performance. Investigating whether certain leadership strategies or structural adaptations can restore the positive impact of EDC in failing organizations could offer practical solutions for companies facing such crises. Finally, integrating a more comprehensive approach that explores the direct relationship between EDCs and broader organizational performance, including financial performance, market share and long-term profitability, would provide a more holistic view of how dynamic capabilities operate across the organizational lifecycle.

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Food Waste Unveiled: Exploring Consumer Attitudes, Habits, and the Path to Sustainable Food Consumption

Jindrich Spicka [1]

[1] Czech University of Life Sciences Prague, Faculty of Economics and Management, Kamycka 129, 16500 Prague - Suchdol, Czech Republic
ORCID: 0000-0001-5699-9544
e-mail: spickaj@pef.czu.cz

Abstract

This study enriches the current state of knowledge presented in the literature review by investigating how the propensity to waste food is influenced by people's views on food waste, frequency of food purchases, and individual habits related to environmentally sustainable household practices. Binary logistic regression modelling in hierarchical form was developed from 672 completed questionnaires representing the population of the Czech Republic aged 15 and over. The research shows that the propensity to waste food is higher among individuals who are aware of their food waste and concerned about its cost, which can be explained by cognitive dissonance. The phenomenon of forgetting to consume food before it spoils is identified as an important economic reason for food waste, attributed to time inconsistency and imperfect information processing. The frequency of food purchases is found to have a nonlinear relationship with food waste, suggesting an optimal purchase frequency at which individuals can effectively manage their food stocks. Individuals who frequently bring their own bags to the supermarket and regularly sort their waste have lower levels of food waste, driven by pro-environmental behaviour, mindfulness, and adherence to social norms. The study provides practical insights such as educating the public about the environmental impact of food waste, tailoring communication strategies to address cognitive dissonance, developing community programmes that emphasise the social and moral aspects of reducing food waste and fostering a collective sense of responsibility, and implementing economic incentives or penalties to align economic behaviours with environmental and moral values regarding food waste.

Key words

food waste, propensity to waste food, logistic regression, sustainable consumption.

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Introduction

The global push toward sustainability has catalysed fundamental changes across economic, financial, and consumer behaviour domains, particularly within the European Union. As Aleknevičiene and Bendoraityte (2024) emphasise, economic development is now inextricably linked to green initiatives, with environmental protection becoming central to both business strategy and consumer choice (Aleknevičiene & Bendoraityte, 2023). This evolution of consumer consciousness coincides with a growing recognition that sustainable development requires transformative changes in consumption patterns, especially in Central European economies where sustainable practices are still gaining traction (Šálková et al., 2024). Within this context, food waste emerges as a critical intersection of consumer behaviour, environmental impact, and sustainable resource management.

The complexity of consumer decision-making in sustainable food practices is influenced by multiple factors, including price perception, quality assessment, and cultural preferences. Čvirik (2023) demonstrates how perceived price and quality, along with factors such as country of origin, significantly impact purchasing decisions (Čvirik, 2023), while Hála et al. (2024) reveal that even among environmentally conscious Generation Z consumers, various determinants can impede sustainable choices (Hála et al., 2024). This evolving landscape of consumer behaviour is further shaped by technological advancements, with the convergence of FinTech and sustainability creating new pathways for sustainable practices (Ranjan Sethi & Ashok Mahadik, 2024). Research indicates that while consumer interest in ethical and sustainable practices is growing, this awareness does not consistently translate into behavioural changes (Šálková et al., 2024). Understanding the gap between consumer attitudes and actual behaviour regarding food waste requires examining both the barriers to sustainable consumption and the potential solutions emerging from the intersection of technology, finance, and environmental consciousness.

Food waste is a societal issue prevalent in the developed world and a symptom of consumerism and unsustainable consumption. Consumerism, an economic theory, posits that consumer spending – or individual expenditures on goods and services – is the primary driver of economic growth and a key measure of productive success in capitalist economies (Duignan, 2023). Given that consumer spending constitutes a significant portion of the gross domestic product (GDP) in most countries, governments often focus on stimulating consumer expenditure as the most effective means of boosting economic production and increasing GDP.

From a psychological and consumer behaviour perspective, consumerism refers to the collective interest in acquiring goods that may not fulfil genuine needs or desires, sometimes with the conscious (or unconscious) aim of achieving higher social status – a phenomenon American economist Thorstein Veblen termed "conspicuous consumption", arguing that individuals often buy goods not just for their utility but as a display of social status. The modern interpretation of consumerism integrates the idea that higher consumption levels reflect an improved standard of living and enhanced quality of life (Galbraith, 1958). Psychological and behavioural consumerism is a natural, though not inevitable, outcome of policies grounded in economic consumerism (Duignan, 2023).

The theory of consumerism holds that robust consumer spending is the primary engine for economic growth. According to Keynesian economics, aggregate demand, which includes consumer spending, is a key determinant of economic output and employment (Keynes, 1936). A higher demand for products encourages production, leading to job creation and further consumer spending, thereby creating a positive feedback loop that stimulates the economy.

Although consumerism supports economic growth, it also faces criticism. Overconsumption has been linked to environmental degradation, resource depletion, and the development of unsustainable economic practices (Schor, 1998). Critics argue that the relentless pursuit of material goods creates a cycle of debt and inequality, with consumers encouraged to live beyond their means.

Beyond its economic implications, consumerism has become deeply embedded in culture, particularly in the United States. The theory has expanded to explain how consumer choices shape identities, preferences, and social affiliations. Sociologists like Pierre Bourdieu (Bourdieu, 2013) argue that consumption is also a form of cultural capital, where consumer behaviour reflects one's social class, education, and status.

In this context, food waste is seen as a byproduct of consumerism, where overproduction, inefficient supply chains, and consumer behaviours like overbuying lead to the disposal of food. This theory links waste to both economic excess (Abbott, 2014) and the psychology of consumer behaviour (Durante & Griskevicius, 2018).

The issue of food waste is addressed by the global environmental initiative spearheaded by the United Nations through Sustainable Development Goal (SDG) 12, which specifically focuses on responsible consumption and production. SDG 12 is one of the 17 global goals outlined in the United Nations' 2030 Agenda for Sustainable Development. It addresses various aspects of sustainability, including waste reduction and the promotion of efficient resource use. In particular, Target 12.3 aims to "By 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses." This target underscores the need to reduce food waste not only at the consumer level but also throughout the entire food supply chain, from production to distribution and consumption. (United Nations, 2023).

Food waste represents the excessive discarding and loss of food driven by consumer behaviour and systemic inefficiencies. This issue is particularly prevalent in developed countries, where abundant food availability and consumer culture encourage overconsumption and waste. Households are the primary contributors to food waste, underscoring the need to examine the causes and determinants of food waste at the household level more closely (Eurostat, 2023).

Several factors contribute to food waste within the context of consumerism. A key issue on the supply side is overproduction, as food is mass-produced to meet market demand. In some instances, production exceeds actual demand, resulting in surplus food that may remain in storage until discarded. Variability in demand, especially during peak and lean periods, can lead to inefficiencies such as overproduction or underutilization of capacity. By ensuring that supply matches consumer needs, companies can reduce the risk of overstocking and underutilization, which are common drivers of food waste (Kumar, 2017). Furthermore, improving supply chain performance through better demand management enhances customer satisfaction and financial performance, which can promote a more sustainable and waste-conscious supply chain, ultimately reducing the amount of food waste generated in the process (Kumar et al., 2021; Rajani et al., 2022).

Another factor is the relatively short shelf life of food products. Some food is intentionally designed with a limited shelf life to encourage more frequent purchases, which increases the risk of waste if the food is not consumed promptly (Porpino et al., 2015). Alternatively, frozen foods typically have longer shelf lives compared to fresh alternatives, which can help reduce spoilage and waste in households. Understanding the factors that drive consumer adoption of frozen food products can provide insights for manufacturers and marketers to encourage more widespread use, potentially leading to reduced food waste through better preservation and storage options (Arora et al., 2022).

On the demand side, consumer preferences and expectations play a significant role (Wani et al., 2023). Consumers often favour visually perfect food, leading to the rejection of items with minor imperfections or aesthetic flaws, resulting in unnecessary food waste of otherwise edible products. Consumerism also fosters the tendency to purchase more food than is needed, which, if improperly stored or not consumed in a timely manner, can end up in landfills.

While external determinants of food waste, such as demographic and socioeconomic characteristics, are relatively well understood (Jribi et al., 2020; Schanes et al., 2018; Yetkin Özbük & Coşkun, 2020), research on internal subjective determinants has gained traction in recent years. This study seeks to complement the existing literature by examining how the propensity to waste food is influenced by individuals' attitudes toward food waste, consumer shopping behaviour, and environmentally sustainable household practices. Internal subjective determinants are more malleable than external factors, offering opportunities for more effective campaigns and interventions aimed at reducing food waste.

The objective of this article is to identify socioeconomic predictors of food waste levels and explore the underlying motives related to public opinion, consumer purchasing behaviour, and pro-environmental habits. The primary purpose of this research is to clarify the ambiguous significance of environmental, moral, and social motivations in reducing food waste. It is also worthwhile to explore regional differences, particularly comparing significant predictors in the Czech Republic with those in other regions. For instance, personal factors such as employment status, household size, and environmental concerns, as well as established household processes like itemized meal planning, food storage practices, and the reuse of leftovers, were found to be significant only in certain countries (Heng & House, 2022). One limitation of this research is the reliance on self-reported data, which may underestimate the actual amount of food waste while overestimating the associated monetary losses (Elimelech et al., 2019). However, self-reporting questions are a common method in sociological research.

Binary logistic regression is the appropriate method for this analysis, as it allows for identifying the optimal set of parameters (coefficients) that best describe the relationship between independent variables and the probability of consumers being classified into groups – specifically, households with relatively higher or lower levels of food waste compared to those of similar size. To verify the robustness of the model, hierarchical modelling and testing for non-linear relationships were applied. The study utilizes data from the Czech Social Science Data Archive, collected in 2022, representing the Czech population aged 15 and older. The sample is representative in terms of Czech regions, place of residence size, gender, age, and education level. The Czech Republic was chosen as a case study because of its status as an EU member state experiencing economic growth and a rise in consumerism. Over recent decades, the country has seen significant economic development and improvements in living standards, reflected in the expansion of its retail sector, which offers a wide array of goods and services. As an open economy, the Czech Republic has access to both local and multinational products and brands. It shares many commonalities with other EU member states, such as similar lifestyles, consumer habits, and distribution systems. The following literature review delves into the motivations behind food waste and efforts to avoid it, drawing on key empirical studies from recent years. The review provides the foundation for the hypotheses tested in this study. The subsequent data and methods section outlines the research design, sample structure, and the quantitative methods employed to evaluate the hypotheses. The research findings are discussed within relevant theoretical frameworks and compared to existing empirical studies. The study concludes by summarizing key findings, acknowledging limitations, and offering implications for future research.

1. Literature review

The first section of the literature review presents the current findings of empirical research focused on internal subjective determinants of food waste. The second section addresses potential external influences in the form of sociodemographic and socioeconomic variables. The discussion examines how these variables are associated with food waste behavior and whether certain groups are more or less likely to engage in food waste practices.

1.1 Internal determinants (motives) for food waste

A recent systematic literature review explores the use of theoretical frameworks in the design and implementation of food waste reduction programs (Kim et al., 2022). The review identifies a notable lack of theoretical model application in studies addressing food waste behaviours. It finds that deterministic approaches, which focus on how individual thoughts and emotions shape behaviour, are frequently referenced. However, the analysis calls for more trials utilizing stochastic approaches, such as nudge theory, to expand our understanding and strengthen the evidence base on effective theories for altering food waste behaviour. The study emphasizes the importance of incorporating multiple theoretical constructs in program methodologies to enhance the effectiveness of behaviour change strategies aimed at reducing food waste.

In the literature, four primary types of motivations for avoiding food waste are identified: environmental, moral, financial, and social (Ribbers et al., 2023). *Environmental motivation* arises from concerns about the environmental burden posed by food waste. Food production demands significant resources, including land, water, energy, and fertilizers. Food waste is connected to lifestyle sustainability, attitudes toward waste (Liu & McCarthy, 2023), environmental awareness, spatial limitations for recycling, policies, and household time constraints or priorities (Nunkoo et al., 2021).

However, the literature varies in its assessment of whether environmental concern is the primary driver of food waste avoidance (Ribbers et al., 2023). It is essential to consider individuals' knowledge and awareness of the potential environmental impacts of food waste (Graham-Rowe et al., 2014; Knezevic et al., 2019). For instance, distorted environmental awareness can lead to the misconception that food waste naturally decomposes without harming the environment. Consumers are also often unaware of the secondary impacts of food waste when it is packaged and discarded in plastic (Djekic et al., 2019).

A lack of theoretical knowledge about assessing food edibility (Teng et al., 2021) and a poor understanding of food waste (Farr-Wharton et al., 2014) also negatively influence food waste behaviours. The experimental study (Linder et al., 2018) investigates the effectiveness of an informational leaflet in promoting food waste recycling among urban households. Conducted in Stockholm, the study employed a natural field experiment and utilized a difference-in-difference analysis to assess the leaflet's impact. The results revealed a significant increase in food waste recycling and a reduction in overall household waste within the treatment group compared to the control group, demonstrating the leaflet's effectiveness in encouraging sustainable waste management behaviours.

Additionally, automatic motivations, such as consumer habits and routines (González-Santana et al., 2022) and automatic barriers related to concerns about pests, odours, poor hygiene, and local authority capabilities in food waste collection (Allison et al., 2022), are important contributing factors. Clarifying the ambiguous role of environmental motivations in reducing food waste is one of the objectives of this research.

Moral motivation, on the other hand, is linked to conscience, concern, and feelings of guilt toward those who lack adequate access to food. Moral motivation to prevent food waste in households is related to food security, ethical treatment of animals, addressing social justice issues, environmental stewardship, responsible behaviour, respect for food's intrinsic value, and recognition of the efforts of those involved in food production (Richter & Bokelmann, 2018). When consumers are aware of the harmful effects of food waste, subjective moral norms (Bretter et al., 2023) and perceived behavioural control positively influence their intention to reduce food waste (H. Wang et al., 2023). However, it is crucial to clarify the focus of moral barriers to food waste, as expressed through various moral constructs (Ribbers et al., 2023).

Some studies include measures of moral norms related to a sense of responsibility for preventing food waste and guilt regarding hunger (P. Wang et al., 2021), while others incorporate environmental factors (Stancu et al., 2016) or moral obligations to purchase "suboptimal" food (Aschemann-Witzel et al., 2018). The ambiguity in the relationship between moral norms and food waste is further supported by the discrepancy between stated intentions and actual behaviours. Although consumers may perceive food waste as immoral, this intuitive moral imperative alone is often insufficient to reduce food waste (Gjerris & Gaiani, 2013).

One of the most common reasons for food disposal includes expired expiration dates and perceived signs of spoilage, such as undesirable odours and tastes (Djekic et al., 2019). Additionally, the frequency of grocery shopping influences the amount of household food waste, though not necessarily the tendency to purchase discounted products (Giordano et al., 2019).

Financial motivation is a significant factor and involves concerns about the cost of discarded food. For many individuals, saving money appears to be a more powerful motivator than environmental or moral concerns (Graham-Rowe et al., 2014; Neff et al., 2015). Most qualitative and quantitative studies agree that price-sensitive consumers are less prone to food waste (Ribbers et al., 2023).

By reducing food waste, households can save money by maximizing the use of purchased food. For example, an Australian study found that food storage practices, reuse of leftovers, eating behaviours, food expenditures, and grocery shopping frequency all significantly impact household-level food waste (Ananda et al., 2021). Proper meal planning, ingredient storage, cooking techniques, and leftover utilization can help reduce food expenses and minimize waste (Aloysius et al., 2023; dos Santos et al., 2022; Principato et al., 2021).

Physical capabilities, such as managing food waste through home composting or feeding pets, along with the time and financial costs involved, are significant barriers to food waste recycling in the United Kingdom (Allison et al., 2022). On one hand, food waste is associated with financial losses (Amirudin & Gim, 2019; Stangherlin & De Barcellos, 2018). On the other hand, food waste recycling incurs financial costs, which should be borne by other market participants, such as retailers (Graham-Rowe et al., 2014).

Financial motivations, including the notion that "time is money," also influence decisions about discarding food. Leftovers can save individuals time if there is enough for a complete meal and no future meals are planned. Furthermore, if a meal is prepared at home, time costs are already associated with its preparation, and individuals may be less inclined to waste leftovers (Ellison & Lusk, 2018).

Social motivation for avoiding food waste involves self-presentation, particularly how individuals are perceived by others in relation to social norms (Principato et al., 2021). Injunctive norms, which stem from the expectations of others – regardless of whether these individuals follow such norms themselves – are especially important (Ribbers et al., 2023). However, adherence to social norms often conflicts with consumer convenience, which negatively affects food waste behaviours (Celestino et al., 2022). Efforts to improve personal image can encourage individuals to engage in community initiatives, such as community gardens, food rescue programs, or sharing surplus food. Social motivations, although not extensively explored in the literature, have not been highlighted as primary drivers of food waste avoidance (Graham-Rowe et al., 2014; Grandhi & Appaiah Singh, 2016; Van Geffen et al., 2020).

1.2 External factors of food waste (demographic and socio-economic influences)

Food waste is also influenced by consumers' *demographic characteristics*, and decisions to discard food vary depending on contextual factors (Ellison & Lusk, 2018). Among the socioeconomic determinants of food waste, key factors include gender, age, education, housing characteristics, household size, and income level.

Younger individuals (aged 18-44) tend to waste food more frequently than older consumers, likely due to having fewer cooking skills, less available time, and lower marginal productivity in food preparation (Ellison & Lusk, 2018). An Irish study found that young men dispose of food waste unsustainably, despite expressing some level of concern about the issue; however, they take minimal actions to reduce waste at all stages of consumption (Flanagan & Priyadarshini, 2021).

Thus, gender and age can influence food waste, although the relationship with age may not be linear. Increased awareness of nutrition can lead to higher levels of food waste in households with both young and elderly individuals involved in food decision-making, whereas it tends to reduce food waste in households with middle-aged individuals who typically provide for their families. Education also plays a role in food waste, as higher levels of education in nutrition improve individuals' habits in planning household food consumption (Heidari et al., 2020).

Regarding *housing characteristics*, it is important to consider whether consumers reside in densely populated areas (e.g., high-rise apartment complexes) or in more dispersed neighbourhoods with single-family homes. Consumers living in high-rise buildings in densely populated areas are less likely to participate in recycling programs, and improving recycling outcomes in such settings typically requires greater effort and resources (Rispo et al., 2015). Household size also affects the extent of preventable food waste. For example, Danish households consisting of a single individual are less likely to generate preventable food waste compared to households of other sizes (Edjabou et al., 2016).

Additionally, the positive impact of food knowledge on reducing household food waste diminishes as income levels increase (Z. Wang et al., 2023). Wealthier consumers, particularly those with young children who frequently dine out, tend to waste food more often despite claiming to be aware of their food waste habits (Liu & McCarthy, 2023; Szabó-Bódi et al., 2018). Factors contributing to a higher proportion of food being disposed of as general waste include perceived inconvenience in using a dedicated food waste container, living in apartment units, and higher household income (Aschemann-Witzel et al., 2019; Nguyen et al., 2022).

1.3 Research questions

Based on the literature review, the research addresses key questions relating to food waste, consumer behaviour, and sustainability.

1. What are the internal and external determinants of food waste in households?

The literature review highlights studies on both internal subjective determinants (e.g., psychological factors, attitudes, values, and beliefs) and external determinants (e.g., demographic, socioeconomic factors like age, education, and income). These determinants help explain food consumption and waste patterns, as cited in the works of (Jribi et al., 2020; Schanes et al., 2018; Yetkin Özbük & Coşkun, 2020). This study aims to examine how these factors influence household food waste behaviour in the Czech Republic.

2. How do consumer attitudes and habits influence the likelihood of food waste?

The document discusses environmental, moral, financial, and social motivations that impact food waste behaviour (Ribbers et al., 2023). The role of attitudes toward waste, such as environmental concerns or moral guilt about food disposal, plays a significant role, as suggested by the studies of (Graham-Rowe et al., 2014; Richter & Bokelmann, 2018). The research seeks to investigate these attitudes and their connection to food waste patterns, building on previous theoretical models of behaviour and consumption.

3. What impact do shopping behaviours have on food waste?

Consumer shopping behaviours, like frequency and volume of purchases, can lead to overbuying and subsequent waste (Wani et al., 2023). Previous research has shown that purchasing patterns, driven by sales and aesthetic preferences, contribute significantly to food being discarded. The research examines how these behaviours, such as meal planning, shopping frequency, and decisions around purchasing organic or discounted food, impact the likelihood of food waste.

4. To what extent do environmentally sustainable practices reduce food waste?

The literature review emphasizes the role of environmentally conscious actions, such as waste separation, use of reusable products, and composting, in mitigating food waste. Studies by (González-Santana et al., 2022; Richter & Bokelmann, 2018) note that individuals who adopt pro-environmental habits tend to waste less food. This research aims to link specific sustainable household practices, such as composting and using reusable bags, with reduced food waste.

3. Research Design

3.1 Data and sampling

The primary data source for this research consists of secondary data obtained from the "Foods 2022" survey, which was retrieved from the Czech Social Science Data Archive (CSDA). The CSDA serves as a national data service centre dedicated to the social sciences (Czech Social Science Data Archive, 2022).

The survey successfully gathered data from a total of 821 individuals, representing the population of the Czech Republic aged 15 and above. For each question, respondents had the option to either refuse to answer or indicate that they did not know the answer. Because not all respondents answered all questions, the final sample includes 672 completed questionnaires. Respondents were selected using quota sampling, with quotas established based on region (NUTS 3), size of residence, sex, age, and education. Data collection was conducted through the Computer-Assisted Personal Interviewing (CAPI) method by trained interviewers from the Public Opinion Research Centre of the Institute of Sociology of the Czech Academy of Sciences, between July 14, 2022, and September 4, 2022.

This research focused on various topics, including food waste, shopping and consumption behaviours of Czech households, the disposal of imperfect fruits and vegetables based on appearance, public awareness of the Czech Federation of Food Banks, dietary habits, purchasing behaviours, environmental attitudes and behaviours of Czech society, and public attitudes towards food waste.

The dataset was adjusted through post-stratification weighting to achieve structural representativeness of the Czech Republic's population. Weights were computed using an iterative proportional fitting (raking) method, with the weighting variables including education (four categories) × NUTS 2, age (four categories) × NUTS 2, sex × region, size of residence (eight categories) × age (four categories), and education (four categories) × age (four categories). The Czech Statistical Office provided the data for the weighting, and weight values were constrained to a range between 0.333 and 3.

3.2 Definition of variables

Dependent variable: food waste. The "Foods 2022" database evaluates food waste using two primary measures: (i) the percentage of food discarded by households (measured in intervals) and (ii) a comparative assessment of the proportion of discarded food relative to households of similar size (1 = higher amount of food waste, 2 = same amount of food waste, 3 = lower amount of food waste) computed from (i). Therefore, the dependent variable is not a subjective comparison of the level of household food waste, but rather the comparison of waste levels is based on an interval estimate of household waste across the entire sample (automatic calculation). The second measure, which incorporates a benchmark comparison, is deemed more appropriate as it not only assesses the percentage of discarded food per household, as in the first measure, but also provides a comparison with households of similar size. The authors argue that this approach offers a more comprehensive assessment of food waste, particularly given that benchmark evaluations and comparisons are frequently used in academic literature, such as in the assessment of organizational financial health (Uhlaner et al., 2007).

Due to the relatively small number of respondents who reported discarding a higher amount of food compared to similarly sized households (9.2%), two response categories were consolidated and recoded as follows: 0 = wastes less (representing individuals with lower subjective food waste), and 1 = wastes the same or more (representing individuals with unsustainable food waste behaviours). The two groups are approximately equal in size. By transforming the original variable into a binary form, binary logistic regression can be employed to analyse the model's effectiveness in accurately predicting household membership in the risk group that discards the same or more food than similarly sized households.

The main effects of the research, for which statistical hypotheses were formulated, were divided into three thematic blocks.

Block A. The Public Opinion Research Centre assessed respondents' agreement with statements related to food waste through a series of questions (question codes correspond to those in the original dataset). Respondents rated their level of agreement on a scale from 1 (strongly disagree) to 5 (strongly agree). The frequency distribution of responses to these questions is presented in Appendix A.

- PL_126a Agreement with statement - feels guilty when wasting food.
- PL_126b Agreement with statement - feels remorseful when wasting food because others have nothing to eat.
- PL_126c Agreement with statement - tries not to waste food but still does.
- PL_126d Agreement with statement - could prevent frequent food waste.
- PL_126e Agreement with statement - thinks about the environmental impact of food waste.
- PL_126f Agreement with statement - considers food waste a problem for the environment due to its biodegradability.
- PL_126g Agreement with statement - believes food packaging is worse for the environment than food waste.
- PL_126h Agreement with statement - concerned about the amount of wasted food.
- PL_126i Agreement with statement - only buys products from the shopping list.
- PL_126j Agreement with statement - plans meals in advance for more efficient shopping.
- PL_126k Agreement with statement - buys more than intended when items are on sale.
- PL_126l Agreement with statement - never buys food that is already at home.
- PL_126m Agreement with statement - concerned about the expenses related to wasted food.
- PL_126n Agreement with statement - tries to utilize everything possible when preparing meals.
- PL_126o Agreement with statement - freezes leftovers for later.
- PL_126p Agreement with statement - consumes leftovers the next day.
- PL_126q Agreement with statement - always prepares more food than needed.

- PL_126r Agreement with statement - decides what to discard based on appearance/smell.
- PL_126s Agreement with statement - pays attention to not consuming food after the expiration date.
- PL_126t Agreement with statement - prefers to throw away better quality food than risk consuming something unsafe.
- PL_126u Agreement with statement - forgets to eat food before it spoils.
- PL_126v Agreement with statement - finds it satisfying to empty the refrigerator and get rid of old food.

Block B. Furthermore, consumer shopping behaviour was monitored using four questions (question codes were taken from the original dataset). The frequencies of responses to these questions are provided in Appendix B.

- PL_14: Goes grocery shopping. 1 = Yes, handles all grocery shopping by themselves; 2 = Yes, mostly does the grocery shopping themselves, but others also shop; 3 = Yes, others mostly handle the shopping, but they also shop themselves; 4 = No, never does grocery shopping.
- PL_41: How often they go grocery shopping. 1 = Every day; 2 = Several times a week; 3 = Once a week; 4 = Once every two weeks; 5 = Less often than once every two weeks.
- PL_34: How often they purchase organic food. 1 = Never; 2 = Rarely; 3 = Occasionally; 4 = Frequently; 5 = Always.
- PL_43: Monthly household expenditure on groceries. Eight expenditure levels were monitored (1 = up to 2,000 CZK; 2 = 2,001 - 4,000 CZK; 3 = 4,001 - 6,000 CZK; 4 = 6,001 - 8,000 CZK; 5 = 8,001 - 10,000 CZK; 6 = 10,001 - 12,000 CZK; 7 = 12,001 - 14,000 CZK; 8 = more than 14,000 CZK). The average exchange rate for CZK to USD in 2022, rounded to two decimal places, is 0.04 USD per 1 CZK.

Block C. In the last part, individual habits related to environmentally sustainable household practices were monitored (Appendix C). Respondents indicated the frequency on a scale from 1 = never to 5 = always.

- PL_55a How often do you bring your own bag for shopping?
- PL_55b How often do you buy fruits and vegetables using reusable bags?
- PL_55c How often do you use your own reusable water bottle?
- PL_55d How often do you use environmentally friendly cleaning products?
- PL_55e How often do you prefer to buy food products made in the Czech Republic?
- PL_55f How often do you prepare meals in containers?
- PL_55g How often do you avoid single-use plastic products?
- PL_55h How often do you limit driving a car for environmental reasons?
- PL_55i How often do you save energy and water for environmental reasons?
- PL_55j How often do you separate regular waste for recycling?
- PL_55k How often do you compost?

3.3 Control variables

The literature review findings identify key control variables for the model. These variables include sex, age, education, housing characteristics, household size, economic activity, and household income level. Table 1 provides an overview of the sample's structural characteristics based on these control variables.

- Sex: 1 = male, 2 = female. This is a categorical indicator variable with a reference level of 1.
- Age of the respondent in 2022. This is a scale variable.
- Education according to the International Standard Classification of Education (ISCED): Level 1 = 3C (General Certificate of Secondary Education, International Baccalaureate); Level 2 = 3A/4A (college with A level); Level 3 = 5A (university degree: bachelor's, master's, doctoral degree). This is a categorical indicator variable with a reference level of 1.

- Size of the municipality based on the number of inhabitants. 1 = up to 1,999 inhabitants; 2 = 2,000 - 4,999 inhabitants; 3 = 5,000 - 19,999 inhabitants; 4 = 20,000 - 49,999 inhabitants; 5 = 50,000 - 199,999 inhabitants; 6 = 200,000 and more. This is a categorical indicator variable with a reference level of 1.
- Household size is assessed using two questions.
  - Living with a partner: 1 = yes (58.5%), 2 = no (41.5%). This is a categorical indicator variable with a reference level of 1.
  - Number of household members. This is a scale variable.
- Economic activity of the respondent: 1 = inactive; 2 = active. This is a categorical indicator variable with a reference level of 1.
- Income level is assessed based on the respondent's subjective living standard: 1 = good, 2 = neither good nor bad, 3 = bad. This is a categorical indicator variable with a reference level of 1.

Table 1. Structural characteristics of the sample (N = 672).

Variable	Descriptives
Sex	Male (49.1 %), Female (50.9 %)
Age	Min = 15, Max = 91, Mean = 47.44, Std. Dev. = 17.411
Education	L1 (44.7 %), L2 (33.8 %), L3 (21.5 %)
Size of the municipality	L1 = up to 1,999 (26.2 %), L2 = 2,000-4,999 (12.7 %), L3 = 5,000-19,999 (16.6 %), L4 = 20,000-49,999 (12.7 %), L5 = 50,000-199,999 (12.1 %), L6 = 200,000 and more (19.6 %)
Living with a partner	Yes (58.5 %), No (41.5 %)
Number of household members	Min = 1, Max = 8, Mean = 2.54, Std. Dev. = 1.237
Economic activity of the respondent	No (43.3 %), Yes (56.7 %)
Subjective living standard	Good (58.0 %), Neither good nor bad (34.1 %), Bad (7.6 %)

Source: Author composition.

3.4 Statistical methods

The set of questions assessing the level of agreement with statements about food waste (PL_126a to PL_126v) was subjected to the Kaiser-Meyer-Olkin (KMO) test, a statistical measure used to evaluate the suitability of data for factor analysis (Cureton & D'Agostino, 2013). The resulting KMO value of 0.74 indicates moderate suitability. This suggests that while some manifest variables may be grouped into latent variables, others cannot and should be analysed separately. Consequently, factor analysis was not conducted, and the variables in the PL_126a to PL_126v question set were treated as independent variables.

Given the nature of the dependent variable, binary logistic regression was applied as suggested by recent studies (Abu Hatab et al., 2022; Lang et al., 2020; Tonini et al., 2023). Logistic regression is a statistical method used to estimate the probability of an event (the dependent variable) based on certain known factors (the independent variables) that may influence its occurrence (Pampel, 2000). In this model, the event – whether or not the phenomenon occurred – is represented by a random variable that takes a value of 0 if the event did not occur and 1 if it did. In this case, a code of 0 signifies lower relative food waste compared to similarly sized households, while a code of 1 indicates the same or higher level of food waste. Cases coded as 1 represent households with a higher propensity for food waste.

Logit models use the logistic function to link the linear combination of the independent variables to the probability of the binary outcome. The logistic function is characterized by its "S-shaped" curve, which asymptotically approaches 0 and 1. Mathematically, the logit link function is the log of the odds ratio:

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}} \quad (1)$$

where $\beta_0 + \beta_1 X$ represents the linear combination of predictors.

The error terms (unobserved factors affecting the outcome) in a logit model are assumed to follow a logistic distribution, which has slightly fatter tails compared to the normal distribution (Pampel, 2000).

One way to check robustness is by changing the specification of the model. This involves including or excluding certain variables to see if the results remain consistent. If the key coefficients of interest remain stable across different model specifications, this suggests that the model is robust. Two approaches were applied: 1) Hierarchical modelling, 2) Testing for non-linear relationships. Ad 1)

To check the robustness of the model, the regression analysis was conducted through a series of hierarchical steps (models), which allowed for a more systematic examination of the variables and facilitated the identification of key factors influencing food waste. Hierarchical regression is a statistical method that assesses the relationship between a dependent variable and multiple independent variables, while controlling for the effects of other variables. The primary purpose of hierarchical multiple regression is to evaluate the unique contribution of each independent variable to the prediction of the dependent variable, after accounting for the effects of the other variables (Stam & Elfring, 2008). This approach is widely used in the social sciences and enables comparisons between alternative models, both with and without interaction terms. An interaction effect is present only if the interaction term significantly improves the variance explained in the dependent variable beyond the main effects of the explanatory variables (Veidal & Flaten, 2014). We started with a simple model that includes only control variables, then incrementally added blocks of independent variables (as done in hierarchical regression). If the coefficients for the main variables of interest remain consistent, it indicates robustness.

- **Model 1** includes all control variables in linear form.
- **Model 2** includes all categorical control variables in linear form, while continuous variables (age and household size) are modelled in quadratic form. If no significant influence of the quadratic terms is found in Model 2, only linear relationships will be considered in subsequent models. This approach is consistent with (Cavicchioli et al., 2019).
- **Model 3** includes all control variables and the significant main effects from Block A (agreement with statements about food waste).

H1: People's attitudes toward food waste influence their likelihood of wasting food.

- **Model 4** includes all control variables, the significant main effects from Block A (attitudes toward food waste), and the significant main effects from Block B (consumer purchasing behaviour).

H2: Consumer shopping behaviour influences their likelihood of wasting food.

- **Model 5** includes all control variables, the significant main effects from Block A, Block B, and the significant main effects from Block C (individual habits related to environmentally sustainable household practices).

H3: Individual habits related to environmentally sustainable household practices influence their likelihood of wasting food.

A forward stepwise regression based on the Likelihood Ratio Test was employed to select the main effects in Blocks A, B, and C, as the Wald test may lose power under certain conditions. This process involved calculating logistic regression results for models both with and without the predictor of interest, followed by testing the difference in chi-square values to assess significance (Osborne, 2008).

Ad 2) Testing for non-linear relationships: If continuous variables are modelled linearly, check robustness by including polynomial terms (e.g., quadratic) or by transforming variables (log transformation) to capture potential non-linear effects. We tested the quadratic form of age and number of household members.

After performing the logistic regression, indicators of the predictive ability of the model were calculated. Sensitivity is the probability that the model predicts a positive outcome for a positive object (i.e., correctly classifying a case into the risk group of individuals with a propensity to engage in excessive food waste). Nagelkerke's R^2 is a measure of the goodness of fit in logistic regression analysis. Specificity is the probability that the model predicts a negative outcome for a negative object (i.e., correctly classifying into the group of individuals with a lower propensity to waste food). The cut point probability for classifying a case into the respective group is 0.5. The ROC curve (Receiver Operating Characteristic curve) displays sensitivity against specificity for each cut point. The area under the ROC curve (AUC) is the most commonly used quantitative index describing the ROC curve and also expressing the accuracy of the test. The following threshold values are used for evaluating the test: 0.9-1 excellent, 0.8-0.9 very good, 0.7-0.8 good, 0.6-0.7 sufficient, 0.5-0.6 insufficient (Pampel, 2000). In this study, the area under the ROC curve was calculated for the final Model 5.

The Hosmer-Lemeshow test (H-L) of goodness of fit is used when the outcome variable is binary and when the sample size is sufficiently large to assess the fit of the model to the data.

$$G_{HL}^2 = \sum_{j=1}^{n} \frac{(O_j - E_j)^2}{E_j\left(1 - \frac{E_j}{n_j}\right)} \quad (2)$$

where $O_j = \sum_i y_{ij}$ is the observed number of events in the j-th group. $E_j = \sum_i \widehat{p_{ij}}$ is expected number of events in the j-th group.

If the H-L test statistic is greater than the significance level, we cannot reject the null hypothesis that there is no difference between the observed and expected values predicted by the model. This means that the model estimates correspond to the data at an acceptable level (Hosmer & Lemeshow, 1980).

4. Results

Table 2 provides a comparison of the logit regression models, while Table 3 presents their predictive performance. Model 1 includes all control variables in linear form, and Model 2 incorporates continuous control variables in quadratic form.

Table 2. Results of the logit regression - odds ratios in the Models 1 to 5.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Control					
Sex: F-M	0.644**	0.636**	0.673	0.630*	0.726
Age	0.976***	-	0.987	0.986	0.993
Age (squared)	-	1.000***	-	-	-
Education					
L2-L1	0.870	0.863	0.768	0.755	0.875
L3-L1	0.785	0.763	0.998	0.910	1.170
Size of the municipality					
L2-L1	1.431		1.430	1.603	1.747
L3-L1	0.538*	1.419*	0.507*	0.626	0.541
L4-L1	0.623	0.554	0.554	0.583	0.541
L5-L1	0.742	0.630	0.722	0.830	0.739
L6-L1	1.040	0.764	1.221	1.339	1.132
Living with a partner: No-Yes	0.981	1.031	0.879	0.896	0.989
Number of household members	1.086	-	1.010	1.045	1.099
Number of household members (squared)	-	1.021	-	-	-
Economic activity of the respondent: Yes-No	1.874**	1.761**	1.796**	1.567*	1.622*
Subjective living standard					
Neither good nor bad – Good	1.587*	1.574*	1.369	1.404	1.360
Bad – Good	1.495	1.478	1.879	1.639	1.404

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Main effects: Block A					
PL_126d Could prevent frequent food waste			1.368**	1.362**	1.278*
PL_126m Concerned about the expenses related to wasted food.			1.325**	1.302**	1.310**
PL_126n Tries to utilize everything possible when preparing meals			0.456***	0.447***	0.538***
PL_126u Forgets to eat food before it spoils.			1.520***	1.521***	1.542***
Main effects: Block B					
PL_41 How often they go grocery shopping			-	0.660**	0.667**
Main effects: Block C					
PL_55a How often do you bring your own bag for shopping?			-	-	0.702***
PL_55j How often do you separate regular waste for recycling?			-	-	0.690***
Constant	2.080	1.276	2.049	5.896	34.220
N	672	672	672	672	672

Note: *, ** and ***, denote significance at 10%, 5% and 1%, respectively.
Source: Author composition.

Based on the post-estimation characteristics outlined in Table 3, no significant differences were observed between Model 1 and Model 2. Consequently, only the linear forms of the control variables are examined in subsequent models.

Table 3. Post-estimation statistics for comparable models – logit models.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Nagelkerke's pseudo R^2	0.136	0.135	0.313	0.327	0.380
Sensitivity (%)	60.6	59.9	69.1	68.1	74.9
Specificity (%)	67.3	66.7	71.4	70.4	76.0
Correctly classified (%)	64.2	63.5	70.3	69.3	75.5
Chi-squared	43.479	43.042	107.664	113.318	135.335
-2LL	514.474	514.911	450.289	444.636	422.618
H-L test: chi-sq (p-value)	18.064 (0.021)	18.587 (0.019)	7.808 (0.452)	5.738 (0.677)	3.654 (0.887)

Note: 0.5 cut-off value. Area under Curve (AUC) of the Model 5 = 0.727 (Std. Error = 0.02, p-value = <0.001).
Source: Author composition.

Sex, age, and economic activity emerge as statistically significant predictors of an individual's propensity to waste food. Model 1 shows that women are less likely to waste food compared to men, food waste decreases with age, and economically active individuals have a higher tendency to waste food compared to those who are economically inactive. Additional details on the correlation coefficients of the control variables are provided in the Appendix D.

Age is an important control variable, as it influences whether individuals live with a partner, their economic activity, their standard of living, and the number of household members. As age increases, individuals are more likely to live with a partner, the number of household members decreases (empty nest syndrome), economic activity declines (due to retirement or part-time work), and subjective living standards tend to decrease. A decrease in the number of household members is also associated with a decline in subjective living standards. Thus, age can be considered a key control variable that affects other observed control variables.

After including the main effects in Block A, which express personal opinions related to food waste, age is no longer a statistically significant control variable. However, economic activity remains significant at the alpha = 0.05 level. Individuals who recognize that they waste food and are concerned about the associated expenses exhibit a higher likelihood of food waste (PL_126d: "Frequent food waste could be prevented," odds ratio = 1.368; PL_126m: "I am concerned about the expenses related to wasted food," odds ratio = 1.325). Forgetting to consume food before it spoils is also a significant economic reason for food waste (PL_126u, odds ratio = 1.520). In contrast, individuals who make an effort to use all possible ingredients in food preparation are less likely to waste food (PL_126n, odds ratio = 0.456). Hence, economic factors are the dominant predictors of consumers' propensity to waste food.

The loss of age significance after adding Block A is due to its correlation with several key opinions, including the belief that frequent food waste could be prevented ($r = -0.369$; $p < 0.001$), forgetting to consume food before it spoils ($r = -0.219$; $p < 0.001$), and the effort to use all possible ingredients in food preparation ($r = 0.236$; $p < 0.001$). Older individuals are less likely to acknowledge that frequent food waste can be prevented and are more efficient in using all ingredients during food preparation. They are also less likely to admit to forgetting to consume food before it spoils. Individuals living with a partner tend to be more concerned about the financial implications of wasted food ($r = -0.130$; $p < 0.001$).

Model 4 extends the predictors to include consumer shopping behaviour (Block B). The frequency of grocery shopping is a significant predictor of food waste. A higher score on question PL_41 indicates less frequent grocery shopping, and as shopping frequency decreases, the likelihood of being classified as prone to food waste also decreases (odds ratio = 0.660). However, this relationship is not entirely linear, as shown in Appendix E. Food waste decreases as shopping frequency declines from daily to once a week, but when shopping occurs less frequently (once every 14 days or less), the proportion of wasteful individuals increases. A lower frequency of shopping beyond the optimal level likely leads to excessive stockpiling of ingredients that consumers cannot process in time.

The relationship between grocery shopping frequency and age exhibits a nonlinear pattern (linearity test $F = 0.132$; $p = 0.717$). Older individuals tend to shop once or several times per week (average age 48.35 and 48.78 years, respectively), while younger individuals either shop daily (average age 43.72 years) or less frequently, once every 14 days (average age 43.05 years) or even less frequently (average age 38.33 years).

Model 5, the final model, further extends the analysis by including individual habits related to environmentally sustainable household practices (Block C). Environmental factors play a role in food waste reduction. Individuals who frequently bring reusable bags when shopping (PL_55a, odds ratio = 0.702) and those who regularly separate waste for recycling (PL_55j, odds ratio = 0.690) have a lower propensity to waste food (see Fa and Fb Appendix). Bringing one's own shopping bag instead of regularly purchasing new plastic bags from stores may seem inconspicuous, but it is a significant signal of sustainable behaviour in practice.

There is a significant relationship between the use of reusable bags and age (linearity test $F = 52.891$; $p < 0.001$). The average age of those who never use reusable bags is 33.86 years, while those who always use them are, on average, 51.39 years old. Regarding waste separation, older individuals either do not separate waste at all (average age 50.88 years) or always do so (average age 49.94 years). Younger generations show more uniformity in their waste separation practices.

According to the Hosmer-Lemeshow (H-L) test, Model 5 provides a good fit to the data and can correctly predict nearly three-quarters of individuals who waste food at the same rate or more compared to households of the same size (sensitivity = 74.9%). The area under the receiver operating characteristic (ROC) curve for Model 5 is 0.727, which is considered a strong result.

5. Discussion

The study found that individuals who are aware of their food waste and concerned about the cost of wasted food exhibit a higher propensity to waste food. This behaviour can be explained through the concept of cognitive dissonance, which refers to the psychological discomfort that arises when a person holds conflicting beliefs or engages in behaviours that contradict their values or beliefs (Hinojosa et al., 2017). In this case, people who recognize that they waste food and are concerned about the cost experience cognitive dissonance, as their behaviour of wasting food conflicts with their value of being cost-conscious. To reduce this discomfort, they rationalize their behaviour by continuing to waste food, maintaining consistency between their actions and beliefs. This rationalization can perpetuate a cycle of food waste.

However, alternative explanations exist. First, individuals more aware of their food waste might also be more attuned to environmental or economic concerns, which may introduce a bias in how food waste is measured or perceived. Those more sensitive to waste might overestimate their waste compared to those less aware or concerned, introducing a form of measurement bias (Jones-Garcia et al., 2022). Additionally, food waste could be more a result of ingrained habits and routines than conscious decision-making. People often develop routines around food purchasing and consumption that inadvertently lead to waste, independent of their awareness or concern about costs (Verplanken & Orbell, 2022).

Another explanation involves social influence and peer behaviour. People may be influenced by the behaviour of those around them, making food waste a normalized behaviour, regardless of personal beliefs (Manika et al., 2022). Furthermore, there is often a psychological distance between the act of wasting food and its perceived consequences. While individuals may intellectually understand the cost of food waste, they may not emotionally or practically connect it to their daily behaviours (Aydin & Yildirim, 2021).

One significant economic reason for food waste is that consumers forget to eat food before it spoils. This can be explained by the concepts of time inconsistency and imperfect information processing. Time inconsistency refers to the tendency of individuals to prioritize immediate gratification over delayed rewards (Adams et al., 2014). When faced with the choice between eating food immediately or saving it for later, individuals tend to prioritize immediate consumption, often forgetting to eat the food before it spoils. Additionally, imperfect information processing plays a role; individuals may underestimate how quickly food spoils or overestimate their ability to consume it before it goes bad. This over-optimism can result in unintended food waste.

Individuals who actively try to use all available ingredients during food preparation are less likely to waste food. This aligns with the principle of frugality and resourcefulness. People who make an effort to utilize every ingredient are more mindful of minimizing waste, reflecting a value of efficiency and reducing unnecessary consumption (Shoham & Brenčič, 2004).

Moreover, these individuals likely engage in meal planning and portion control, further reducing food waste. By carefully planning meals and portions, they align consumption with their needs, lowering the chances of excess food going unused (Aloysius et al., 2023).

The frequency of food purchases is a significant nonlinear predictor of food waste, indicating an optimal purchase frequency. Optimal purchase frequency refers to how often individuals can effectively manage their food inventory, minimizing waste while meeting consumption needs (Calvo-Porral & Levy-Mangin, 2016). In the case of food purchases, the optimal frequency is likely to fall within a range where individuals can adequately consume the food before it spoils.

When individuals purchase food more frequently (e.g., daily), they are more likely to buy smaller quantities that align with immediate needs, reducing the likelihood of excess food going unused. As purchase frequency decreases from daily to once a week, the rate of food waste also decreases. However, when individuals purchase food at an extremely low frequency, such as once every 14 days or less, they may struggle to manage their food inventory, leading to excessive stockpiling and increased waste. A significant factor driving this behaviour is consumer stockpiling in response to price promotions (Bell et al., 2002). Therefore, purchase frequency is closely tied to effective planning as a tool for reducing food waste (Aloysius et al., 2023; dos Santos et al., 2022; Principato et al., 2021).

Poor management of the agricultural supply chain, especially in perishable goods like fruits, can lead to significant post-harvest losses, contributing to food waste before products even reach consumers (Kumar & Nath, 2020). A more efficient supply chain that minimizes waste in the production and distribution stages can reduce the amount of food that spoils or is discarded, thus impacting the overall levels of consumer food waste (Kashav et al., 2023; Sharma et al., 2022).

AI-technology-based interventions, particularly those drawing from behavioural theories such as nudging, could be applied to influence consumers' decision-making processes regarding food consumption and waste. By enhancing individuals' awareness and prompting behavioural changes, similar to the effects observed in hospitality settings, AI-driven solutions could potentially reduce food waste by encouraging more mindful consumption patterns (Bangwal et al., 2023).

The final model's findings show that individuals who frequently bring their own bags to the grocery store and regularly sort their waste are less likely to waste food. This can be explained through the concepts of pro-environmental behaviour, mindfulness, and social norms (Dharmesti et al., 2020; Richter & Bokelmann, 2018; Thiermann & Sheate, 2022). Bringing reusable bags and sorting waste are examples of pro-environmental consumer habits that reflect an awareness of environmental issues and a commitment to reducing waste (González-Santana et al., 2022). Individuals who engage in pro-environmental behaviours in one aspect of their lives are more likely to extend this mindfulness to other areas, such as food consumption (Vorobeva et al., 2022). This heightened conscientiousness often translates into reduced food waste.

Frequent use of reusable bags and sorting waste requires individuals to be more mindful of their consumption habits. Mindfulness involves being fully aware of one's actions and their consequences. Individuals who practice mindfulness in their daily routines often extend it to food consumption, becoming more attentive to the amount of food they purchase, serve, and store. This mindfulness helps reduce food waste by promoting more intentional and efficient consumption. Research has shown that people with high mindfulness are more likely to support food waste reduction policies, regardless of the communication method (Olavarria-Key et al., 2021). Additionally, perceived behavioural control and routines related to shopping and reuse of leftovers are significant drivers of food waste, with planning routines contributing indirectly (Stancu et al., 2016).

Social norms and environmental consciousness also influence pro-environmental behaviours, such as bringing reusable bags and sorting waste. When individuals observe others practicing sustainable behaviours or when society encourages these actions through campaigns and regulations, social norms form, promoting these behaviours (De Groot et al., 2021). As a result, individuals who adopt these practices are more likely to engage in other sustainable actions, such as reducing food waste. However, some studies suggest that economic consciousness has a stronger effect than environmental consciousness on the intention to reduce food waste (Graham-Rowe et al., 2014; Neff et al., 2015; Secer et al., 2023).

Among the control variables, age was identified as a key determinant of food waste. Different generations may have distinct attitudes, behaviours, and cultural norms regarding food consumption and waste. Older generations, who may have grown up during times of scarcity or economic hardship, tend to value food more and are less likely to waste it. This is particularly relevant in the Czech Republic, where consumers experienced limited food availability during the pre-1989 socialist period (Ioniță, 2017). In contrast, younger generations, especially those raised in an era of increased environmental awareness, may have a stronger understanding of the environmental consequences of food waste (Ahmed, 2021).

Age is also associated with lifestyle factors that influence food waste (Aschemann-Witzel et al., 2021). Younger adults or individuals with busy lifestyles may have less time to plan meals, shop efficiently, or manage perishable food, leading to impulse purchases and higher food waste (González-

Santana et al., 2022). Conversely, older adults tend to have more established routines and cooking habits, as well as better meal planning skills, all of which contribute to reducing food waste.

Economic activity is another significant predictor of food waste. Economically active individuals, such as those working full-time or with demanding schedules, are more likely to waste food than economically inactive individuals. Time constraints often limit their ability to plan meals, shop thoughtfully, or cook at home, leading to a reliance on convenience foods, takeout, or eating out (Liu & McCarthy, 2023; Szabó-Bódi et al., 2018). These food options, often served in larger portions or pre-packaged, can result in excess food and increased waste.

Conclusions

The study provides insights into the determinants of food waste and offers theoretical explanations for the observed patterns. The findings suggest that the propensity to waste food is shaped by factors such as cognitive dissonance, time inconsistency, imperfect information processing, and the principles of frugality and resourcefulness. People's attitudes toward food waste significantly affect their likelihood of wasting food (H1). Specifically, individuals who are aware of their food waste and concerned about the associated costs may experience cognitive dissonance, leading to a rationalization of their behaviour, which perpetuates the cycle of food waste. Additionally, food wastage driven by economic factors can be explained by time inconsistency and imperfect information processing, where individuals prioritize immediate consumption and underestimate the rate at which food spoils. In contrast, individuals who emphasize using all available ingredients and engage in meal planning and portion control are less prone to waste, reflecting values of efficiency and minimizing unnecessary consumption.

The study also underscores the role of food purchasing frequency in influencing food waste. Consumers' shopping behaviour significantly affects their propensity to waste food (H2). There appears to be an optimal purchasing frequency at which individuals can effectively manage their food inventory and minimize waste. As the frequency of purchases decreases from daily to weekly, food waste tends to decline. However, when purchasing frequency drops below optimal levels, such as once every 14 days or less, the likelihood of food waste increases due to the accumulation of excessive raw materials that individuals may not have time to consume before spoilage occurs.

Moreover, pro-environmental behaviours, such as regularly bringing reusable bags and sorting waste, contribute to reducing food waste. Individual habits related to environmentally sustainable household practices significantly impact their propensity to waste food (H3). These behaviours are associated with increased environmental awareness, mindfulness, and adherence to social norms that promote sustainability.

Additionally, age and economic activity emerged as key control variables in the analysis. Older individuals and those who are economically inactive tend to generate lower levels of food waste, likely influenced by generational differences, lifestyle factors, resource management practices, and heightened awareness of waste-related issues.

Understanding these determinants of food waste can inform interventions and strategies aimed at reducing waste throughout the food system, from production to consumption. Addressing cognitive dissonance, promoting mindful consumption, emphasizing the optimal frequency of purchases, encouraging resourcefulness, and fostering pro-environmental behaviours can all contribute to mitigating food waste and promoting more sustainable consumption practices.

The study makes a significant theoretical contribution to the field of sustainable consumer behaviour, particularly in the context of food waste. It addresses a critical gap in the existing literature by examining both internal subjective determinants (such as personal views on food waste, cognitive dissonance, and individual habits) and external factors (including socioeconomic influences) that shape food waste behaviour.

This comprehensive approach extends beyond the typical focus on demographic and socioeconomic characteristics by exploring the psychological and behavioural dimensions that influence food waste. By employing binary logistic regression models and analysing data from a representative sample of consumers in the Czech Republic, the study provides valuable insights into the motivations driving food waste, including cognitive dissonance and economic factors. The findings reveal the complex interaction between awareness, attitudes, and habits in determining an individual's propensity to waste food, underscoring the importance of targeted interventions and strategies aimed at reducing household food waste.

The originality of the study lies in its holistic examination of the diverse factors contributing to food waste behaviour, offering a nuanced understanding that is essential for developing effective waste reduction strategies. This theoretical contribution deepens our knowledge of the drivers behind food waste, which is crucial for addressing this pressing issue in the broader context of global sustainability challenges.

Several successful initiatives from various countries offer valuable insights that could be adapted to the Czech context. For instance, France's pioneering 2016 law requiring supermarkets to donate unsold food to charities has resulted in a 22% increase in food donations, demonstrating the effectiveness of legislative approaches. In Denmark, the "Stop Wasting Food" (Stop Spild Af Mad) movement has successfully reduced household food waste by 25% through public awareness campaigns and partnerships with retailers, particularly by promoting the sale of imperfect produce at discounted prices. Similarly, South Korea's implementation of the "Pay as You Throw" system, where households are charged based on the amount of food waste they generate, has led to a 10% reduction in food waste within its first year of implementation. The Netherlands has demonstrated success through its "United Against Food Waste" program, which brings together businesses, research institutions, and government agencies to create innovative solutions, resulting in a 29% reduction in consumer food waste between 2016 and 2022. Italy's approach combines tax incentives for food donations with simplified donation procedures, leading to a 40% increase in recovered food since 2018. In Australia, the "Love Food Hate Waste" campaign has successfully engaged over 137,000 households through practical education programs, cooking workshops, and digital tools for meal planning, achieving an average reduction of 15% in household food waste. These initiatives align with our findings in the Czech Republic, where consumer awareness and economic incentives were identified as key drivers of food waste reduction. The success of these international programs suggests that a multi-faceted approach combining legislation, public education, and economic incentives could be particularly effective in the Czech context. Notably, the Danish and Dutch models of stakeholder collaboration could be especially relevant, given the similar market structure and consumer behaviours observed in our study.

This research on food waste, consumer attitudes, and sustainable consumption offers several potential benefits to society. The study highlights how food waste contributes to environmental degradation by wasting resources like water, land, and energy. By identifying key factors that lead to food waste, the research can inform strategies to minimize waste at the household level, thus helping reduce the carbon footprint and the strain on natural resources. By examining consumer attitudes, shopping habits, and pro-environmental behaviours, the study provides insights into how individuals can be encouraged to adopt more sustainable consumption practices. For example, using reusable bags, composting, and better meal planning can be promoted to reduce waste. The study identifies financial motivations as a key driver of food waste, showing that households often waste food due to poor planning or buying too much. By promoting better food management and reducing food waste, the research can help households save money.

The research can inform policymakers and businesses about the societal and economic costs of food waste. Policymakers can use the findings to develop regulations or incentives to reduce food waste, such as supporting food recovery programs or encouraging retailers to sell "imperfect" produce. By highlighting the importance of food waste recycling and sustainable household practices, the research supports the concept of a circular economy, where resources are reused and repurposed, rather than wasted.

The study highlights moral and social motivations for reducing food waste, such as guilt over global hunger or concern for environmental degradation. By understanding these motivations, initiatives can be designed to foster a stronger sense of social responsibility regarding food waste.

The research clarifies the previously ambiguous roles of environmental, moral, and social motivations in food waste reduction. It reveals that cognitive dissonance plays a significant role among individuals who are aware of and concerned about food waste yet continue to engage in wasteful practices due to economic considerations. The study emphasizes the influence of economic factors, such as forgetting to consume food before it spoils, and highlights the positive impact of environmentally conscious behaviours, like bringing reusable bags to stores, in reducing food waste. By elucidating these motivations and behaviours, the research offers practical insights for developing effective strategies to combat food waste. Specifically, the study suggests:

- Educating the public on the environmental consequences of food waste to cultivate a deeper sense of moral responsibility and promote pro-environmental behaviours.
- Designing communication strategies that address cognitive dissonance by aligning individuals' environmental and moral beliefs with their actual food consumption and waste behaviours.
- Creating community programs that emphasize the social and moral dimensions of reducing food waste, fostering a collective sense of responsibility.
- Implementing economic incentives or penalties to better align economic behaviour with environmental and moral values concerning food waste.

The research has several limitations. First, the study is based on a specific sample from a single country, which limits the generalizability of the findings to a broader international population. It is important to recognize that different demographic groups, cultural contexts, and socioeconomic factors can influence food waste behaviour, and the study's sample may not fully capture the diversity of these influences across countries.

Second, the study relied on self-reported data, which can be subject to biases and inaccuracies, particularly social desirability bias (Cerri et al., 2019). While this research focuses on individuals' subjective opinions rather than objectively measurable food waste, participants may have been inclined to provide socially desirable responses. This could lead to an underreporting of food waste behaviours or an overstatement of pro-environmental actions, potentially affecting the accuracy of the data and distorting the findings. Future studies might consider using objective measures or observational data, such as waste compositional analysis, to validate self-reported information (Quested et al., 2020).

Finally, the study did not account for all control variables that could potentially influence food waste behaviour, as it was based on secondary data. Incorporating additional control variables in future research could provide a more comprehensive understanding of the determinants of food waste.

This study has provided valuable insights into the determinants of food waste, offering important implications for understanding consumer behaviour and informing waste reduction strategies at both the individual and household levels. However, several areas remain for further investigation. As this study focused on a specific context, cultural and contextual factors may influence food waste differently across regions or countries. Future research could explore how cultural norms, values, and societal attitudes toward food waste affect consumer behaviour. Examining the role of cultural factors in shaping attitudes, practices, and perceptions of waste could aid in developing more effective strategies tailored to specific cultural contexts.

Since aging populations are becoming more prominent globally, studying the relationship between food waste and aging can yield valuable insights. One of the research ideas could investigate how retirement affects food consumption and waste patterns. As individuals retire and their daily routines change, they may have more time for meal planning, food preparation, and efficient food use. This could lead to reduced food waste. Close to this topic, researchers could also study the relationship between loneliness, social isolation, and food waste among older adults. Older adults living alone may experience different food waste patterns due to cooking for one person or lacking the motivation to prepare meals. Finally, it would be good to explore how dietary restrictions and health-conscious food choices among aging populations influence food waste. Older adults often adjust their diets due to health conditions (e.g., low-sodium or diabetic diets), which might lead to food waste if specific food items are not consumed in time.

Another valuable study could assess the effectiveness of technological tools, such as smart refrigerators, meal-planning apps, or reminders, in reducing food waste in aging households. Technology may help older individuals better manage their food inventory, reducing forgotten or spoiled food. However, there might be a learning curve or access issues.

Investigating the underlying decision-making processes that contribute to food waste could also yield valuable insights for designing interventions. Future studies could examine the cognitive and psychological factors that influence consumer decisions related to food purchasing, consumption, and waste. Understanding how elements such as habit formation, decision heuristics, perceived behavioural control, and subjective norms shape food waste behaviour could help in developing targeted interventions that address these cognitive processes.

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Personal and Institutional Barriers Perceived by Staff of Latvian Higher Educational Institutions in the Process of Digital Transformation: Pilot Survey Results

Jeļena Titko [1,*], Nataļja Verina [2], Jūlija Mironova [3], Kristīne Uzule [4], Žanna Čerņostana [5]

[1] EKA University of Applied Sciences, Riga, Latvia
ORCID: 0000-0003-1333-0941
e-mail jelena.titko@eka.edu.lv

[2] EKA University of Applied Sciences, Riga, Latvia
ORCID: 0000-0003-2106-8314
e-mail natalija.verina@eka.edu.lv

[3] ISMA University of Applied Sciences, Riga, Latvia
ORCID: 0000-0002-3090-6220
e-mail mironovai.julijai@gmail.com

[4] EKA University of Applied Sciences, Riga, Latvia
ORCID: 0000-0002-2633-6069
e-mail kristine.uzule@eka.edu.lv

[5] Baltic International Academy, Riga, Latvia
ORCID: 0000-0002-9366-1259
e-mail: zanna.bki@inbox.lv

[*] Corresponding author: Jelena Titko, jelena.titko@eka.edu.lv

Abstract

The research goal is to evaluate personal and institutional barriers towards digital transformation (DT) as perceived by different groups of staff at Latvian higher educational institutions (HEIs). Initially, a comprehensive literature review was conducted, followed by a survey, using the research instrument (questionnaire) developed by the authors. Academic and administrative staff members from Latvian HEIs participated in the survey. For the purpose of evaluation, data were processed by means of frequency analysis and procedures of comparing independent samples. From the viewpoint of staff, the most significant institutional barriers to digital transformation are a lack of financial resources, a lack of time (lack of human resource capacity or overloading with existing tasks), and employees' motivation in general. In turn, a lack of time, a lack of management support, and a lack of IT skills were identified as the most significant personal barriers. The research is limited by the sample size. However, this pilot study was aimed at technical testing of the measurement scale and preliminary testing of some hypotheses. Managers of higher educational institutions could use the results of the presented research to facilitate the digital transformation process and develop DT-related strategies. This research distinguishes itself from other research by the context (field of higher education) and localisation (there are a limited number of studies in the field of DT in Latvia).

Key words

higher education institution; digital transformation; barriers.

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Introduction

The urgent need for digital transformation (DT) in education arose during the COVID-19 pandemic, when most educational institutions were forced to switch to remote learning (Tadesse, S. & Muluye, 2020; Pokhrel & Chhetri, 2021; Algahtani et al., 2023; Bates, 2023; Carroll & Constantinou, 2023).

The focus in this research is on higher education (HE). There is a wide range of papers and reports devoted to the issues of DT specifically in the HE fields (Bond et al., 2018; Benavides et al., 2020; Gaebel & Morrisroe, 2023; Antonopoulou et al., 2023). Barriers to implementing digital transformation in organisations have also been discussed by many researchers (Egala et al., 2024; Trenerry et al., 2021). However, there are a limited number of studies in the field of DT in Latvia. Most studies conducted by Latvian researchers or containing information about Latvia highlight the issues of DT in secondary education. The most frequently debated topics are the professional development of teachers, digital competences, and digital inclusive education (OECD, 2023; Laganovska, 2021). Higher education is not a priority topic and is covered in a small number of articles (Rubene et al., 2021; Nimante, 2019). The latest report available on the webpage of the Latvian Ministry of Education and Science about the digitalisation of Latvian higher education dates from 2020 (PWC, 2020).

The research goal is to evaluate personal and institutional barriers towards digital transformation (DT) as perceived by different groups of staff at Latvian higher educational institutions (HEIs). The authors used a bespoke questionnaire. The list of barriers was substantiated during a previous study (Uzule & Verina, 2023).

The research is limited by sample size: only 42 representatives of six Latvian HEIs (both private and public) participated in the survey. However, this pilot study was aimed technically at testing the measurement scale and the preliminary testing of some hypotheses. The plan was to conduct a cross-country study and investigate the impact of respondent profile on perceptions of barriers.

At the initial stage, the research revealed that the most significant institutional barriers to digital transformation are a lack of financial resources/lack of investment in digital transformation, a lack of time (a lack of human resource capacity or overloading with existing tasks), and employees' motivation in general. In turn, a lack of time, a lack of management support, and a lack of IT skills were identified as the most significant personal barriers.

The paper contains five main parts. The Introduction is followed by the Literature Review, which provides a theoretical background on digital transformation in higher education, as well as examining institutional and personal barriers identified by other researchers. The Methodology part describes the research instrument and provides the results of the internal consistency test. The research hypotheses are also formulated in the Methodology section. The Results section summarises the key outcomes of the survey, indicating the most significant barriers to digital transformation as perceived by the staff of Latvian HEIs. The Conclusion part discusses the practical implications of the research and directions for further investigation.

1. Literature review

1.1 Digital transformation in higher education

Digital transformation involves the evolutionary process driven by digital technologies, reshaping organisations both internally and externally to create new pathways for value creation (Vial, 2019). This organisational change, facilitated by digital technologies, has the potential to reshape every aspect of an organisation to fully leverage its core competencies (Antonopoulou et al., 2023) through more effective decision-making (Hassan et al., in press) and enhanced governance (Niu et al., 2023). Digital transformation is required for the rapid adaptation to market changes to sustain a competitive advantage at individual, business and system levels (Chen et al., 2024), thus improving profitability and asset quality (Chao et al., 2024). Businesses embracing digital transformation boost their capacity to create innovations (Chen et al., 2023; Niu et al., 2023), which results in new products and services consistent with the latest customer preferences (Uzule & Verina, 2023). The shift towards digital transformation requires strategic change and management of all organisational operations (Hess et al., 2016).

Higher education institutions (henceforth HEIs) are no exception (Gobble, 2018). Digital transformation at HEIs typically aims to improve three areas of operations – teaching, learning and administrative processes (Gilch et al., 2020), which, consistent with the findings of Wang, Hong, et al. (2023), could be translated into three key drivers of digital transformation: curriculum development and adaptation, the integration of digital technologies for widespread educational use, and the utilisation of cloud computing. Digital transformation in HEIs entails integrating various business activities, processes, and employee competencies with system applications and information technology (Benavides et al., 2020). As part of their digital transformation strategy, HEIs aim to attract top talents across different roles, including researchers, academic staff, office administrators, and students (Elliot et al., 2016). Another aspect of digital transformation strategy focuses on enhancing relationships, both internally and externally, through HEI setups. This setup fosters stronger connections with stakeholders and enables more efficient interaction channels, aligning with the evolving practices in experience management (Seres et al., 2018). The ongoing transformation of technology infrastructure and stakeholder management approaches in HEIs significantly shapes outcomes and organisational culture, affecting the use of technologies in teaching and learning processes (Sandkuhl & Lehmann, 2017).

Research on digital transformation in higher education has unveiled diverse dimensions. Overall, four distinct categories could be identified. Firstly, studies focusing on educational technology and usage, such as those by Bond et al. (2018) and McKnight et al. (2016), shed light on how technology is utilized by both educators and students to enhance learning experiences and outcomes. The second dimension focuses on digital transformation processes and outcomes, as investigated by Licka and Gautschi (2017), who surveyed the transformation within higher education institutions, revealing its impact on universities, the labour market, and the economy. Furthermore, Selwyn (2016) contributes to understanding stakeholder views and experiences, offering insights into the varied perspectives on digital transformation and student perceptions of technology use. Finally, KPMG (2018) examines sectoral disparities, highlighting differences between the education sector and other economic sectors in their digital transformation efforts. Collectively, these dimensions provide a comprehensive understanding of the multifaceted nature of digital transformation in higher education.

Thus, implementing digital transformation in HEIs presents challenges linked to the constraints of educational services (Benavides et al., 2020). Nevertheless, HEIs pursue digital transformation despite various challenges (Antonopoulou et al., 2023; PwC, 2018) due to the promise of enhanced organizational efficiency and effectiveness (Benavides et al., 2020). HEIs cannot avoid digital transformation, given the imperative of preparing students with qualifications and skill sets relevant to digital or hybrid environments (Wang, Li, et al., 2023). Consequently, many HEIs are actively developing digital strategies to navigate the complexities of the transformation process and leverage its potential benefits (Wang, Li, et al., 2023).

1.2 Barriers to digital transformation in higher education institutions

Digital transformation, a phenomenon altering business operations (Chen et al., 2024), is associated with various issues and risks across various industries (Hassan et al., in press; Wang et al., 2024) and is accompanied by both positive and negative attitudes, resulting in barriers to digital transformation implementation. Such barriers, generating uncertainty (Chen et al., 2024) throughout organizational activities, can be categorized as institutional and personal.

Institutional barriers to digital transformation in higher education encompass a range of challenges rooted in organizational dynamics and resource constraints. These barriers are multifaceted and impact various aspects of the digital transformation process. One set of institutional barriers pertains to the lack of adequate technological infrastructure and tools essential for effective operations in digital spaces, which includes issues such as limited access to diverse digital platforms and insufficient workplace equipment, internet infrastructure deficiencies and insufficient reliability in connectivity (Boychuk et al., 2022; Mall & Haupt, 2022; Mikheev et al., 2021). Additionally, digital security concerns pose a notable barrier to digital transformation efforts (Wang et al., 2024).

Another set of constraints include insufficient financial resources for technological investment (Hassan et al., in press; Wang et al., 2024) and comprehensive digital training essential for enhancing digital competencies among academic and administrative staff (Mall & Haupt, 2022). Academic staff should be able to effectively use digital tools and co-create educational content with digital solutions to enhance the quality of education and learning experience. Considering continuous upgrades in technologies as well as the lack of relevant digital competences of staff, HEIs encounter the issue of continuous investment into their staff training. Without institutional support, digital experience and relevant methodology, poor digital skills of staff would not reach a necessary level soon (Boychuk et al., 2022; Hassan et al., in press) especially considering a digital divide between younger more digitally savvy students and more experienced but less digitally advanced staff (Henderson et al., 2015; Wilms et al., 2017).

Institutional barriers to digital transformation in higher education also encompass organizational, communication, and collaboration impediments (Boychuk et al., 2022; Wang et al., 2024). These barriers manifest as deficiencies in organizing study processes, such as inadequacies in creating conducive exam environments and maintaining bidirectional and continuous communication channels with students, which is why students may experience detachment from the learning process, impacting their engagement and academic outcomes (Boychuk et al., 2022; Jamah et al., 2022). Addressing these organizational and communication challenges is crucial for fostering a supportive and interactive learning environment conducive to effective digital transformation in higher education.

Other constraints include regulatory and market demands. Regulatory and policy barriers further complicate digital transformation efforts, often due to the fragmentation of policies, leading to uncertainty regarding compliance and implementation (Hassan et al., in press). Market risks, job losses among staff, and evolving customer demands pose significant challenges, particularly in higher education, where resistance to user-friendly and efficient digital solutions can impede progress (Hassan et al., in press; Wang et al., 2024). This resistance underscores the importance of enhancing the quality of technologies, methodologies, and competencies among academic and administrative staff to meet market expectations.

The success of digital transformation initiatives in education is closely tied to heads of institutions (Cheng & Wang, 2023), specifically, their vision and leadership styles. The leadership's commitment to innovation and adaptation is crucial for overcoming resistance to change and driving digital integration efforts forward. This perspective aligns with the innovation diffusion theory, which posits that the adoption of innovation, including digital transformation, is influenced by social norms and organizational structures (Wang, Hong, et al., 2023). As such, effective leadership plays a pivotal role in shaping the organizational culture and facilitating the diffusion of digital technologies throughout HEIs over time.

Personal barriers pertaining to digital transformation encompass individual factors such as employee and student knowledge, skills, attitudes, and behaviour affecting their engagement with digital transformation initiatives within the workplace. Personal barriers stem from insufficient digital skills of staff (Hassan et al., in press) and their inexperience in digital spaces (Boychuk et al., 2022) as well as attitudinal and behavioural resistance (Mikheev et al., 2021), having roots in fear of job loss (Hassan et al., in press), poor digital literacy and lack of opportunities to develop digital competencies. In HEIs, academic and administrative staff and students might have various levels of digital skills at the onset and during digital transformation as well as various levels of capacity to advance their digital competences due to generational differences (Englund et al., 2017; Scott et al., 2017).

Some barriers to digital transformation simultaneously impact both institutional and personal levels, as highlighted in recent research (Chen et al., 2023; Hassan et al., in press; Wang et al., 2024). A lack of data, entrenched corporate traditions, and cultural norms contribute to a limited understanding of how digital tools can positively impact business processes, which hinders the implementation of digital transformation activities (Hassan et al., in press). Finally, effective digital transformation strategies for education hinge upon three key pillars: investment in technology, transformation of people, and enhancement of processes (Lakshmi et al., 2023). The success of these strategies relies heavily on the quality of data analytics, which affects the overall customer experience. An organization's ability to overcome barriers to digital transformation is intricately linked to various cross-structural and cross-capacity factors, encompassing the adoption of new technologies, the digital competencies of employees, and the efficacy of decision-making processes (Uzule & Verina, 2023). The integration of innovative technologies with digital transformation has the potential to improve the quality of education, fostering new educational models that prioritize innovation and foster heightened levels of student engagement (Wang, Hong, et al., 2023).

2. Materials and methods

To achieve the research goal, the authors conducted a survey among staff of Latvian HEIs. Theoretical background for the development of the research instrument (questionnaire) was provided in Uzule and Verina (2023). The structure of the questionnaire is reflected in Table 1.

Table 1. Structure of the questionnaire.

Part	Question	Type of the question; responses
A	Respondent profile	Age, gender, education level, HEI, position, work experience
B	Institutional barriers	22 barriers. Evaluation scale: level of agreement (1 – absolutely disagree; 5 – absolutely agree)
C	Personal barriers	18 barriers. Evaluation scale: level of agreement 1 – absolutely disagree; 5 – absolutely agree)

Source: Authors' developed.

The respondents were offered to evaluate each barrier by using a five-point scale (1 –completely disagree; 5 – completely agree). Before data processing, the instrument (B and C measurement scales) was tested for internal consistency using Cronbach's alpha (Table 2).

Table 2. Internal consistency of B scale.

B scale. Labels	Cronbach's Alpha if Item Deleted	C scale. Labels	Cronbach's Alpha if Item Deleted
IT knowledge	0.944	Cybersecurity	0.909
Information	0.943	External control	0.901
Understanding DT processes	0.942	Job loss	0.905
Infrastructure	0.941	Income reduction	0.906
Data security	0.945	IT skills	0.900
Traditions	0.944	Learning-teaching activities	0.908
Vision	0.945	Management support	0.906
Digital culture	0.941	Family support	0.903
Financial risk	0.948	Self-efficacy	0.902
Risk of failure	0.946	Openness to change	0.902
Fear	0.944	Time	0.905
Understanding about DT potential	0.942	Anxiety	0.904
Financial resources	0.943	Motivation	0.905
Time	0.943	Willingness	0.905
Management engagement	0.942	Limitations	0.905
Training programs	0.942	Financial barriers	0.906
Motivation	0.943	Technical support	0.905
Communication	0.942	Traditions	0.907

Coordination	0.942	
Understanding of purpose	0.941	
Staff resistance	0.943	
DT standards	0.941	

Source: Compiled by the authors.

The value of Cronbach's Alpha for the whole B and C scales was 0.945 and 0.909 respectively, what points to the very high internal reliability. The analysis of the measure "alpha if item deleted" pointed to good relevance of all statements.

Survey data was processed by means of frequency analysis. The only the answers "4" (agree) and "5" (completely agree) have been analysed by the authors in order to rank the statements in the scales.

Two specific hypotheses have been formulated to test the difference in evaluations of institutional and personal barriers by different groups of staff members representing higher education institutions. First hypothesis was formulated based on the results of Eurobarometer (European Commission, 2017), which revealed "...large differences in perceptions ... across countries, and between people of different age groups and educational backgrounds", and the findings of Swiss researchers (Seifert, & Charness, 2022) who discovered that "...perceived ease of use is related to age, socioeconomic status, health, and interest in technology". Four age groups were defined: 1) < 25 years old; 2) 26-41; 3) 42-58; 4) over 59 years old.

H1: There is a difference in perception of digital transformation barriers by staff members representing different age groups.

In formulation of the second hypothesis, the authors based mostly on their subjective viewpoint about perception of changes, incl. digital transformation, in higher education institutions within different groups of staff:

H2: There is a difference in perception of digital transformation barriers by administrative and academic staff members.

However, this hypothesis can be supported also by findings of other researchers. For instance, Schraeder et al. (2006) revealed that "...employees who were engaged in making decisions related to the technology changes reacted more positively to the changes than individuals with lower levels of involvement. Mainly, the second hypothesis has been formulated based on the following statement made by Van Der Schaft et al. (2024): "Whereas management might see digital transformation as an inevitable and logical form of change for their organization, employees' buy-in cannot be taken for granted as their perceptions and interpretations vary and may differ from management's claims."

To test the difference in perceptions of institutional barriers and personal barriers to digital transformation by different age groups, as well as by administrative and teaching staff, Mann-Whitney U test was performed. The selection of the non-parametric technique has been substantiated by the results of the Shapiro-Wilk test. In all cases, $p<0.05$ indicated that data did not follow a normal distribution.

3. Results

Table 3 summarizes the results of the frequency analysis, taking into accounts only respondents who were "agree" or "completely agree" with the B and C scale statements.

Table 3. Results of frequency analysis.

Institutional barriers	% of respondents who agreed with the statement	Personal barriers	% of respondents who agreed with the statement
IT knowledge	30%	Cybersecurity	32%
Information	25%	External control	27%
Understanding DT processes	20%	Job loss	17%
Infrastructure	42%	Income reduction	20%

Data security	32%	IT skills	37%
Traditions	15%	Learning-teaching activities	29%
Vision	39%	Management support	42%
Digital culture	22%	Family support	20%
Financial risk	32%	Self-efficacy	22%
Risk of failure	20%	Openness to change	17%
Fear	10%	Time	63%
Understanding about DT potential	22%	Anxiety	20%
Financial resources	54%	Motivation	29%
Time	68%	Willingness	20%
Management engagement	24%	Limitations	17%
Training programs	39%	Financial barriers	32%
Motivation	51%	Technical support	32%
Communication	32%	Traditions	12%
Coordination	42%		
Understanding of purpose	49%		
Staff resistance	42%		
DT standards	42%		

Source: Compiled by the authors.

Based on respondents' answers, both institutional and personal barriers can be categorized according to the frequency of responses, which indicate the perceived importance or strength of barriers. The first three categories can be identified within the top 50% of the most frequently mentioned responses. For institutional barriers, where the highest frequency was 68%, the top 50% ranged from 34% to 68%. For personal barriers, where the highest frequency was 63%, the top 50% ranged from 31.5% to 63%. Within these ranges, categories were divided into three equal parts based on frequency.

The most frequently cited barrier, appearing in over 60% of responses for both institutional and personal categories, was time (68% and 63%, respectively).

For institutional barriers, the next most common factors included financial resources, motivation, and understanding of the purpose. The issue of insufficient funding to support digital transformation was highlighted also in the study of Gkrimpizi & Peristeras (2022). Regarding the motivation (IB – 51%), these results are aligned with studies performed by Deloitte (Hagel, 2019) and Robertsone & Lapina (2022).

In the third frequency category, respondents identified factors such as staff resistance, digital transformation (DT) standards, coordination, infrastructure, vision, and training programs. Regarding personal barriers, after time, the second category included management support, while the third category incorporated IT skills, cybersecurity, financial barriers, and technical support. Overall, the key barrier across both categories was time. Other common factors identified in the second and third categories included financial constraints and technical infrastructure and support. Unlike personal barriers, institutional barriers also highlighted factors related to staff characteristics.

The lower level of 50% of the responses ranged between 10% and 32% for institutional barriers, and 12% and 29% for personal barriers. Considering the raw percentage value, these barriers can be viewed as low priority, which is why even though they can be categorized by frequency, it might be also reasonable to group them by content. Under such categorization, the barriers could be grouped into organizational, competence, psychological, social, and economic factors.

Organizational factors encompass the barriers of data security, financial risk, communication, management engagement, digital culture, understanding the potential and processes of digital transformation (DT), risk of failure, traditions, technical support, external control, and limitations.

Competence factors include IT knowledge, information, learning-teaching activities, and self-efficacy, which are essential for equipping individuals with the necessary expertise and confidence to engage effectively in digital transformation processes.

Psychological factors involve fear, anxiety, motivation, willingness, and openness to change, highlighting the personal and emotional responses of individuals towards digital transformation, which can significantly influence their engagement and acceptance of new technologies. Social factors include family support, indicating the role of personal relationships and social backing in an individual's ability to cope with and embrace digital transformation.

Economic factors address concerns about income reduction and job loss, focusing on the financial implications and job security issues that may arise as a result of digital transformation initiatives. This comprehensive categorization helps in understanding the multi-faceted nature of digital transformation and the various dimensions that need to be considered for its successful implementation.

For testing of the hypotheses, a non-parametric Kruskal-Wallis Test was applied. The difference in perception of barriers towards digital transformation within different age groups was discovered only in case of the barrier “IT skills”. The evaluation of this barrier by representatives of the age group “42 to 58 years old” was statistically higher than evaluation by other age groups (Table 4). So, the conclusion is that the first hypothesis (H1: There is a difference in perception of digital transformation barriers by staff members representing different age groups) is rejected.

Table 4. Kruskal-Wallis H test results: grouping variable – age.

Institutional barriers			**Personal barriers**		
	Kruskal-Wallis H	**Asymp. Sig.**		**Kruskal-Wallis H**	**Asymp. Sig.**
IT knowledge	1.659	0.436	Cybersecurity	1.962	0.375
Information	3.133	0.209	External control	0.334	0.846
Understanding DT processes	2.594	0.273	Job loss	0.130	0.937
Infrastructure	0.051	0.975	Income reduction	1.208	0.547
Data security	0.654	0.721	IT skills	6.410	**0.041**
Traditions	0.441	0.802	Learning-teaching activities	3.217	0.200
Vision	1.768	0.413	Management support	3.077	0.215
Digital culture	3.200	0.202	Family support	4.824	**0.090**
Financial risk	1.966	0.374	Self-efficacy	0.501	0.779
Risk of failure	1.918	0.383	Opennes to change	0.030	0.985
Fear	0.280	0.869	Time	0.635	0.728
Understanding about DT potential	1.923	0.382	Anxiety	1.121	0.571
Financial resources	2.432	0.296	Motivation	0.516	0.773
Time	0.074	0.964	Willingness	0.082	0.960
Management engagement	2.074	0.355	Limitations	0.559	0.756
Training programs	3.855	0.146	Financial barriers	1.144	0.564
Motivation	4.910	**0.086**	Technical support	4.085	0.130
Communication	0.832	0.660	Traditions	1.691	0.429
Coordination	0.157	0.924			
Understanding of purpose	0.273	0.872			
Staff resistance	0.411	0.814			
DT standards	0.860	0.650			

Source: Compiled by the authors.

With the lower confidence, the difference was revealed in case of the institutional barrier "Lack of an appropriate motivation system to stimulate employees to engage in DT processes" (Motivation) and personal barrier "Lack of family support (family members against the teacher spending his home time on IT skills training)" (Family support).

The difference in perception by academic and administrative staff was revealed in case of only two statements (Table 5). The second hypothesis (H2: There is a difference in perception of digital transformation barriers by administrative and academic staff members) is also rejected.

Table 5. Kruskal-Wallis H test results: grouping variable – position.

Institutional barriers			**Personal barriers**		
	Mann-Whitney U	**Asymp. Sig. (2-tailed)**		**Mann-Whitney U**	**Asymp. Sig. (2-tailed)**
IT knowledge	186.500	0.541	Cybersecurity	169.000	0.279
Information	198.000	0.766	External control	207.500	0.968
Understanding DT processes	148.000	0.100	Job loss	192.000	0.641
Infrastructure	173.000	0.329	Income reduction	207.500	0.967
Data security	181.000	0.438	IT skills	172.000	0.322
Traditions	127.000	**0.021**	Learning-teaching activities	180.000	0.432
Vision	170.500	0.303	Management support	172.000	0.320
Digital culture	185.000	0.509	Family support	180.500	0.436
Financial risk	169.500	0.287	Self-efficacy	164.500	0.228
Risk of failure	187.000	0.553	Opennes to change	206.000	0.935
Fear	188.000	0.566	Time	196.500	0.735
Understanding about DT potential	140.000	**0.062**	Anxiety	157.500	0.163
Financial resources	194.000	0.686	Motivation	190.500	0.620
Time	204.500	0.902	Willingness	137.000	**0.050**
Management engagement	209.000	1.000	Limitations	191.500	0.634
Training programs	183.000	0.487	Financial barriers	166.500	0.251
Motivation	172.000	0.314	Technical support	203.500	0.883
Communication	176.000	0.376	Traditions	170.000	0.281
Coordination	186.500	0.548			
Understanding of purpose	192.500	0.659			
Staff resistance	192.000	0.649			
DT standards	204.500	0.903			

Source: Compiled by the authors.

1. Scale B "Keeping traditional principles (management believes that digital transformation is not necessary)". Academic staff members evaluated this barrier higher. This means that more academic staff agree with this statement compared to administrative staff.
2. Scale C "Lack of willingness". Results show that administrative staff evaluated willingness for digital transformation statistically higher than academic staff. This barrier seems more significant for administration.

Conclusions

Digital transformation has been underway; however, its progress varies due to numerous impeding factors. Earlier, Uzule and Verina (2023) distinguished digital transformation barriers into institutional and personal categories. This research continued that study, aiming to evaluate these barriers as perceived by different staff groups in Latvian higher educational institutions (HEIs).

The survey results identified the ranking of barriers based on response frequency. The primary barrier for both institutional and personal categories was time. Financial barriers and technical infrastructure & support factors were significant for both institutional and personal barriers, forming a second tier when combined due to the minimal difference. However, institutional barriers also included issues related to personal and professional traits of staff members. Barriers with a frequency below 30% were grouped into organizational, competence, psychological, social, and economic factors. Organizational barriers included data security, financial risk, communication, management engagement, digital culture, and risk of failure. Competence barriers involved IT knowledge, information, learning-teaching activities, and self-efficacy. Psychological barriers encompassed fear, anxiety, motivation, willingness, and openness to change, while social barriers included family support. Economic factors addressed concerns about income reduction and job loss. This comprehensive categorization provides a deeper understanding of the multifaceted nature of digital transformation and highlights the various dimensions that need to be considered for its successful implementation.

The research also tested two hypotheses and found differences in the perception of barriers between academic and administrative staff. Academic staff perceived adherence to traditional principles as a more significant barrier, while administrative staff viewed the lack of willingness for DT more critically. Age-related differences were notable only in the evaluation of IT skills, particularly among the 42 to 58 age group. Considering that the differences were revealed regarding the small number of statements, the research hypotheses have been treated as rejected.

Although the small sample size limits the generalizability of these findings, the results underscore the complexity of digital transformation and the importance of addressing both institutional and personal barriers.

This research offers several important implications and benefits for higher education institutions aiming to navigate the complexities of digital transformation. First, by identifying time constraints as the most significant barrier, institutions can prioritize time management strategies and streamline processes to facilitate smoother digital transitions. Recognizing the importance of financial resources, motivation, and understanding the purpose highlights the need for strategic investment and clear communication of digital transformation goals to all stakeholders. The categorization of barriers into organizational, competence, psychological, social, and economic factors provide a holistic framework for HEIs to develop targeted interventions. For instance, enhancing IT knowledge and self-efficacy through comprehensive training programs can address competence-related barriers, while fostering a supportive digital culture can mitigate psychological resistance. Addressing economic concerns such as job security can help alleviate financial anxiety among staff, promoting a more accepting attitude towards digital changes.

Finally, the research underscores the necessity of differentiated strategies for academic and administrative staff, as well as for various age groups. Tailoring approaches to the specific needs and perceptions of these groups can enhance the effectiveness of digital transformation initiatives. Overall, this study is a platform for further investigation. The next steps for this research include: 1) enlarging the sample size and testing hypotheses about differences in the evaluation of barriers towards digital transformation based on all profile characteristics (age, gender, education level, position, work experience); and 2) conducting a cross-country study to compare results between countries. Currently, the authors have agreements with the European Digital Learning Association, Trakia University – Stara Zagora (Bulgaria), Ilia State University (Georgia), National University "Yuri Kondratyuk Poltava Polytechnic" (Ukraine), Universidad Católica de Valencia (Spain), University of Galati (Romania), Hadassah Academic College (Israel), and Università di Urbino Carlo Bo (Italy).

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Real Convergence in the European Union – the Social Dimension

Alina Grynia [1,*], Jacek Marcinkiewicz [2]

[1] Faculty of Economics - Informatics, Branch of the University of Bialystok in Vilnius, Lithuania
ORCID: 0000-0002-3349-7020
e-mail: grynia@uwb.edu.pl

[2] Faculty of Economics and Finance, University of Bialystok, Poland
ORCID: 0000-0003-4701-8155
e-mail: j.marcinkiewicz@uwb.edu.pl

*Corresponding author: Alina Grynia, grynia@uwb.edu.pl

Abstract

Real convergence is a multidimensional process of drawing European Union (EU) member states closer together, which takes place in many aspects, including economic and social ones. In social terms, it means improving living conditions and reducing social inequalities. Real individual consumption in EUR per capita with purchasing power parity was used as the variable informing about the level of social development. The main objective of the article is to verify the existence of social convergence between EU member states (including the United Kingdom – UK) between 2004 and 2023. Two methods of convergence measurement were used to analyse convergence: beta and sigma types. Convergence calculations were based on data from Eurostat. In the case of missing data (UK), projections were made using growth rates from the previous period. The analysis was supplemented by the Shannon entropy index. The study's application objective was to assess whether the scale of the reduction in the gap in individual consumption (well-being and quality of life) is narrowing, including identifying periods when convergence has been slower. This can help guide future economic policy and measures to further narrow the gap. In addition, the authors distinguish countries that have managed to improve their position to the greatest extent in terms of the analysed measure of social development.

Key words

social convergence, catching up, Actual Individual Consumption per capita, European Union, Shannon entropy index.

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Introduction

The European Union's cohesion policy aims to ensure economic, social and territorial cohesion, promoting sustainable territorial development. In 2015, UN member states adopted the world development strategy to 2030, Transforming our World: The 2030 Agenda for Sustainable Development, containing 17 Sustainable Development Goals. The resulting development priorities reflect the three dimensions of sustainable development: economic, social and environmental. While promoting economic growth (and productivity) has always been an objective of EU policy, there is now a strong orientation towards the social dimension of development in member countries. The elimination of poverty in all its forms and dimensions has been identified as the greatest global challenge and a necessary requirement for sustainable development (UN, 2015).

The global challenges of the past two decades, including the financial crisis, the COVID-19 pandemic and the war in Ukraine, have impacted individual EU countries to varying degrees, revealing large income disparities. Between 2006 and 2021, the share of people living below the poverty line increased in two-thirds of the member states and income inequality increased in about half of the countries (especially in the "old" member states) and decreased in the other half (especially in Central and Eastern Europe) (Eurofound, 2024).

In the context of high social inequalities, the harmonisation of living standards between EU countries and the strengthening of socio-economic growth as well as convergence become essential. Economic convergence should be accompanied by social convergence (Moscovici, 2017). These two dimensions of convergence are complementary and lead to sustainable development. The prerequisite for building social well-being is economic well-being. Convergence is therefore a multidimensional process of convergence between EU countries in many areas. In addition to the economic and social dimensions already mentioned, the institutional, environmental, or cultural dimensions are also important. In the most general terms, social convergence is understood as the improvement of living conditions and the reduction of social inequalities. It may relate to poorer countries catching up with more developed economies or to economies becoming more similar in the long term in relation to the indicator analysed (Wójcik, 2018).

The overall intention of the authors is to verify the existence of social convergence within EU member states (including the UK) between 2004 and 2023. Two types of convergence are considered: beta (less developed countries show faster growth rates than more developed countries) and sigma (differentiation decreases over time). In addition, the analysis was enriched by the Shannon entropy index. The study of social convergence was performed on the basis of changes in real private consumption at purchasing power parity, equating it with a measure of household material well-being. This indicator, estimated by Eurostat, refers to all goods and services actually consumed by households in EU countries. It therefore includes not only goods and services purchased directly, but also services provided by the state, such as those relating to health care or education.

The analysis consists of two stages. In the first, the hypothesis of an equalisation of welfare and quality of life (measured by the real private consumption index) between EU countries was verified based on the concept of sigma convergence. In the second, using the convergence beta and the Shannon entropy index, the divergence in development between EU member states was assessed, identifying the countries that managed to improve their position to the greatest extent in terms of the measure of social development analysed.

1. Literature review

1.1 Economic Background

In general, the term convergence is used to describe the process by which initially dissimilar phenomena (objects) become similar in terms of some studied characteristic. In the economic sciences, this concept has become established since the 1990s with the development of economic growth theory. Real convergence concerns permanent structural changes in a given economy (region, group of countries) and the equalization of real values (Wójcik, 2018). Real social convergence is understood as the equalisation of the population's standard of living (material well-being) measured by Actual Individual Consumption (AIC) with purchasing power parity (PPS) – AIC per capita (PPS).

The starting point for the analysis of the relationships between the member states are the differences in AIC per capita in relation to the EU average (EU=100) in 2004 and 2023, which are presented in Table 1.

Table 1. Real individual consumption per capita and its evolution (considering purchasing power parity) of the EU countries and the UK in 2004 and 2023, (in % of EU average, change in percentage points – pp.).

Countries	2004	2023	Change 2004-2023	Countries	2004	2023	Change 2004-2023
Belgium	116.3	120.0	3.8	Lithuania	55.4	89.1	33.7
Bulgaria	40.2	65.1	24.9	Luxembourg	181.5	155.5	-26.0
Czechia	71.0	81.5	10.5	Hungary	61.6	67.0	5.4
Denmark	121.9	119.3	-2.6	Malta	88.4	91.8	3.3
Germany	124.3	115.5	-8.8	Netherlands	129.1	122.3	-6.8
Estonia	53.5	80.7	27.3	Austria	124.4	118.9	-5.6
Ireland	120.1	115.9	-4.2	Poland	56.1	81.7	25.6
Greece	103.1	80.6	-22.6	Portugal	92.2	87.0	-5.2
Spain	101.3	90.4	-10.9	Romania	39.1	82.4	43.3
France	113.2	107.5	-5.7	Slovenia	83.1	88.3	5.2
Croatia	61.0	77.8	16.8	Slovakia	53.4	75.9	22.5
Italy	116.5	102.0	-14.5	Finland	111.2	110.3	-0.9
Cyprus	101.1	105.3	4.2	Sweden	125.7	109.4	-16.3
Latvia	47.9	70.6	22.6	UK	139.6	101.5	-38.2

Source: own elaboration on the base of Eurostat (2023).

Meanwhile, Figure 1 illustrates the changes in individual consumption per capita of the EU countries and the UK in the period 2004–2023.

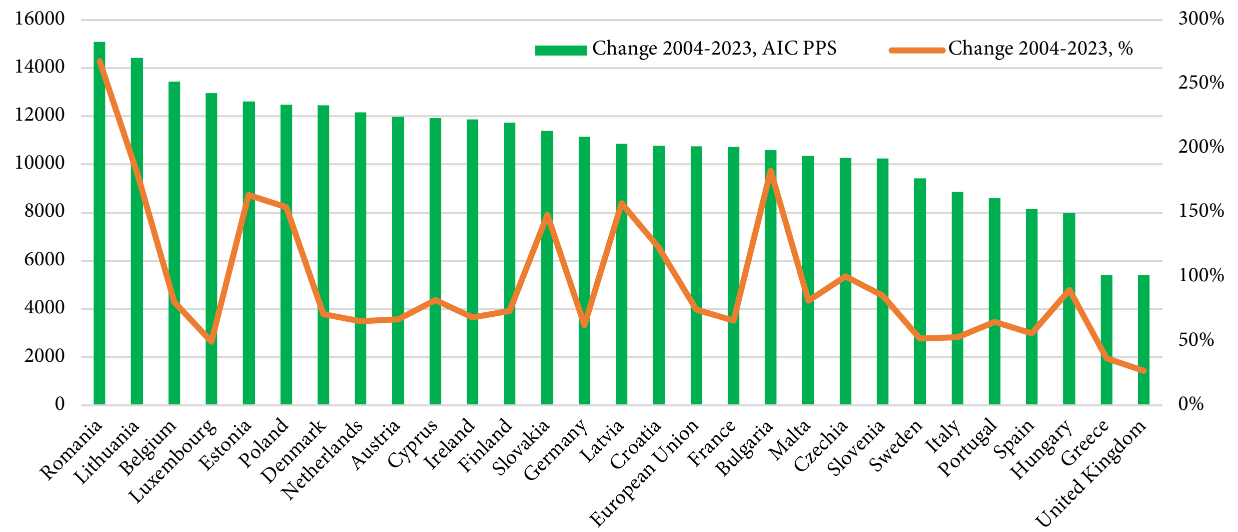

Figure 1. Change in private consumption per capita in EU countries and the UK in the period 2004-2023, (AIC per capita, euro PPS and %).
Source: own elaboration on the base of Eurostat (2023).

The empirical picture emerging from the above information allows us to note that:

1. Taking real individual consumption into account, Luxembourg is still the wealthiest country in the EU, but is now not as far ahead of the others as it was at the beginning of the period under review. In 2023, the country's AIC per capita exceeded the EU average by 55.5%, compared to 81.5% in 2004. A similar situation is characteristic of many wealthier countries.
2. The group of countries that exceed the EU average in terms of consumption has decreased. AIC per capita was above the EU average in 2004 in 15 countries - from Luxembourg (81.5%) to Cyprus (1.1%). In general, this group included the "old" EU countries, except for Portugal (92.2%). Of the "new" countries, only Cyprus was classified in this group. Meanwhile, in 2023, AIC per capita was above the EU average in only 13 countries, including the UK, but these values were much lower - from 55.5% (Luxembourg) to 1.5% (UK). Two "old" countries - Spain and Greece -

moved to the group below the average. Meanwhile, the "new" member states, except for Cyprus, are still in the group below, but are quickly approaching the average level of the entire group.

3. The fastest real convergence process took place between 2004 and 2023 in Romania and Lithuania, with increases of 43 and 34 percentage points (pp.) respectively, as well as in Estonia (27 pp.), Poland (26 pp.), Bulgaria (25 pp.), Latvia and Slovakia (23 pp.), as well as Croatia (17 pp.). In contrast, negative changes in the ratio of the national AIC to the EU average were recorded for several countries - the UK (down 38 pp.), Luxembourg (26 pp.), Greece (23 pp.), Italy (15 pp.) and Spain (11 pp.) - which (from their point of view) would imply a slowdown in the pace of convergence.
4. Worthy of separate mention is the spectacular success of Romania, which in almost two decades was able to reduce the development gap with the EU by more than 43 p.p., and the consumption of the average Romanian increased by 15,089 euros (in PPS). In the pre-accession period (2004-2007), a significant upward trend was already visible, and in three years it managed to reduce the gap with the EU average by 9.5 pp. (a similar result was achieved by the Czech Republic in the whole 2004-2023 period). On joining the EU, Romania was approaching 50% of the Community level, and in 2023 the country's individual consumption level was 82.4%. Romania's performance has been the subject of a number of studies, which also highlight the significant regional disparities in the country's socio-economic development, as real convergence at regional level is not progressing at the right pace (Munteanu, 2015; Chilian et al., 2016). While this is characteristic of most EU countries, research shows that less developed countries, such as Romania, have higher levels of regional disparities (Fitekova et al., 2021).

On the basis of the data presented, it is possible to see large differences in the initial level of real individual consumption and in the rate of closing the gap in material well-being, the living standards of EU residents. At the same time, the preliminary analysis of the changes taking place suggests the existence of a clear social convergence between the EU member states (including the UK) in the period 2004-2023. It is also worth noting that after the EU enlargement the pace of convergence of the "new" countries accelerated, which can be treated as a positive impact of membership in the integration grouping. In this case, European integration acts as a "motor of convergence", accelerating progress (Stojkov et al., 2024). It therefore makes sense to analyse in greater depth the processes of social convergence taking place, using selected methods to measure it.

1.2 Real social convergence

Most common in the economic literature are studies of real economic convergence. These concern studies of how countries are becoming more similar in terms of economic development, most often income convergence based on changes in GDP per capita or labour productivity. Less frequently, convergence analysis is also concerned with other factors of economic growth (output of different sectors of the economy, public finances, inflation, trade balance, the role of institutions, sustainable production and others) (Rapacki&Próchniak, 2019; Holobiuc, 2021; Matkowski et al., 2016; Józwik, 2017; Lungu, 2024; Bobeva, 2021; Cabral&Castellanos-Sosa, 2019; Markowski et al., 2023; Toplu, 2022; Fedajev et al., 2021).

Much less frequently, convergence analysis concerns social phenomena. However, assuming that GDP per capita is a rather unreliable measure of well-being or standard of living, because a high level of economic development measured by GDP does not mean a high level of consumption and does not indicate the material well-being of residents (Stiglitz et al., 2009), researchers increasingly often refer to real social convergence.

The approach to this issue is characterised by great diversity both in the context of the choice of variables studied, the territorial and temporal scope of the conducted research, and the results of the analysis. The existence of various approaches to measuring social convergence results from the lack of a single, universal definition of the standard of living of the population (Kuc, 2014). Most often, empirical analyses devoted to real social convergence focus on income, individual consumption or other socio-economic phenomena, such as human and social capital, unemployment and poverty, education and health care, and other variables. In this case, convergence is examined for each of the selected variables or a synthetic variable constructed on the basis of several partial factors is used.

The review of studies on the above-mentioned topics showed that the assessment of the convergence of social development between Member States is most often made on the basis of an assessment of the social dimension and problems of inequality in European countries in the context of the assumptions of the EU cohesion policy. Dubra (2016) analyses a number of indicators characterising the social situation in EU countries, as well as GDP growth, population income levels, unemployment rates and welfare in relation to the targets. Finding the existence of convergence in terms of the areas studied, the author concludes that the speed of convergence depends on the initial disparity in the level of development in EU countries, and that the European convergence policy needs to be improved through an appropriate selection of country-specific social measures.

Similarly, the article by Lafuente et al. (2020) assesses the poverty and social exclusion pillar of the Europe 2020 strategy, analysing whether it has contributed to convergence between EU countries between 2005 and 2018. The authors conclude that convergence occurs in heterogeneous clubs and through a catch-up process among Eastern European countries. In contrast, convergence within each club is not accompanied by a trend towards club convergence. This indicates, according to the researchers, a multi-speed Europe, which casts doubt on the sustainability of the entire convergence process in the EU.

This framework includes the research by Wnorowska et al. (2019) seeking an answer to the question of whether social convergence occurred in the EU-28 in the context of implementing the recommendations and objectives of social policy formulated within the framework of the "Europe 2020" strategy in the years 2010–2016. A few indicators for material deprivation, education level and employment were selected for analysis. The authors conclude that within the analysed indicators it cannot be unequivocally stated that convergence in the EU-28 countries occurs in the social area. Positive changes were noted in the level of education, while at the same time there was divergence on the labour market.

Kramkowska & Mikiashvili (2021) studied the convergence of post-socialist countries (11 EU countries, seven Eastern European countries and seven Asian countries) between 2000 and 2018 in terms of economic, social and environmental well-being, as well as economic freedom based on selected indicators, such as: Human Development Index, Environmental Performance Index, Economic Freedom of the World. The research showed that the countries included in the study are definitely converging in terms of socio-economic well-being, environmental performance and economic freedom. However, the speed of convergence varies, with post-socialist EU countries scoring higher on these three indices than other post-socialist countries.

An analysis of the social convergence of the Baltic countries for the period 1995-2015 in the context of catching up with the "old" member states, in particular the Scandinavian countries, can be found in the work of Masso et al. (2019). Another interesting research thread is the search for the relationship between economic and social convergence. The authors indicate that the convergence process takes place within the examined social and labour market indicators at different speeds. In addition, it is very likely that not all differences between European countries will decrease only due to income convergence. Individual mechanisms by which convergence can occur may also pose certain challenges, e.g. social dialogue. Similar studies were conducted for individual Baltic countries - Lithuania (Grynia, 2018) and Latvia (Dubra, 2014).

A noteworthy study is that of Kluth (2023), in which the author set the objective of determining the level of social and economic convergence of the European Union countries and its changes in the period 2000-2022. To achieve the objective, a synthetic measure of social and economic development was constructed using various methods of normalisation and a ranking of countries was created. Changes in the ranking positions of individual economies allowed conclusions to be drawn about the existence of convergence in the group of 28 countries studied, with a weakening of the pace during periods of economic, financial and military crises.

2. Methodology

Social convergence refers to the changes taking place in the societies of the countries being compared in terms of improving their living conditions and reducing social inequalities. For the purposes of this article, real social convergence is understood as the narrowing of the gap between countries in terms of the level of social welfare as measured by a selected indicator. For the analysis, the index of real individual consumption per capita in euro estimated by Eurostat with purchasing power parity was chosen, which allows for a comparison between countries (AIC per capita in PPS). Unlike other measures characterising the degree of satisfaction of consumption needs (e.g. the Household Final Consumption Expenditure indicator), it expresses the value of goods and services actually consumed by households regardless of the source of their financing. They may be covered by household disposable income or financed by the state, local government or other institutions. It thus makes it possible to compare the actual standard of living in different countries, disregarding differences in the activity of governments as providers of certain services. We equate this indicator here with the material well-being of Europeans.

There are a number of methods for measuring convergence that correspond to different theoretical concepts of convergence, but the most recognised and most widely used by researchers are beta (β) and sigma (σ) type convergence. They represent the classical approach to convergence analysis and the concept of beta convergence originated from neoclassical economic growth models (Mankiw et al., 1992; Sala-i-Martin, 1996; Barro& Sala-i-Martin, 2004). In the most general terms, the first one (β) refers to a faster growth of the analysed indicator in a country with a lower initial level, while the second one (σ) denotes a reduction in the variation of levels between countries. Initially, these research methods were used to analyse economic convergence, but later they were adapted to analyse social convergence (Hobijn, 2001; Mazumdar 2002; Neumayer 2003; Berbeka, 2006; Kusideł, 2013; Kuc, 2014; Grynia, 2018).

The aim of the study in this article is to simultaneously verify two types of social convergence: beta and sigma type for the period 2004-2023 in the European Union countries based on a variable reporting the level of social development (AIC per capita in PPS). β-convergence occurs when less developed countries show a faster growth rate of the variable than more developed countries. To verify β-convergence, the following regression equation was estimated:

$$\frac{1}{T}\ln\frac{y_T}{y_0} = a_0 + a_1 \ln y(0) + \varepsilon_i \tag{1}$$

where y(T) – individual consumption per capita at purchasing power parity in the final year of the i-th country; y(0) – individual consumption per capita in PPS in the initial year of the i-th country; T – number of years between the final and initial years; ε_i – random component. Convergence β occurs when the evaluation of the parameter α_1 is negative and statistically significant. In such a situation, the rate of convergence coefficient β can be calculated from the formula:

$$\beta = -\frac{1}{T}\ln(1 + a_1 T) \tag{2}$$

A so-called half-life index was also estimated, which determines the time needed to reduce existing developmental differences by half according to the formula:

$$T_{0,5} = -\frac{\ln(0,5)}{\beta} \tag{3}$$

Meanwhile, σ-convergence occurs when the differentiation of a variable (AIC per capita in PPS) decreases over time. Variability can be measured:

a) the standard deviation of the natural logarithms of the variable according to the formula:

$$\mathrm{sd}(\ln y\,(t)) = \alpha_0 + \alpha_1 t + \varepsilon_i \tag{4}$$

where sd(lny (t)) - standard deviation of the natural logarithms of the variable in year t.

b) coefficient of variation, i.e. relative standard deviation according to the formula:

$$V_s = \frac{sd}{\bar{X}} = \alpha_0 + \alpha_1 t + \varepsilon_i \tag{5}$$

where sd– standard deviation, $\bar{X}$– arithmetic mean of the variable in year t.

The variable t on the right side of the equation is the time variable (a linear regression is assumed), and ε_i is a random component. The standard deviation of the variable is not used to measure sigma convergence because of its tendency to increase with time.

The article simultaneously verifies both types of social convergence due to the links between them: the condition for sigma convergence is beta convergence, while beta convergence can occur in a country where there is a development gap in relation to the reference group of countries. Additionally, the analysis was extended by estimating the Shannon entropy index.

Shannon's entropy theory (Shannon, 1948), derived from thermodynamics, has been applied in many fields of science, including economics. There are examples of the application of the entropy method both in the analysis of regional development (Czyż & Hauke, 2015; Liang et al., 2017), as well as in the analysis of spatial differences for a group of selected countries (Villas-Boas et al., 2019) or for all European Union member states (Fedajev et al., 2021).

A similar approach in the study of social convergence was also used in this article. The entropy index is used here as a measure of the divergence between EU countries in terms of real individual consumption in euro per capita. The countries studied were divided into 4 groups based on the value of AIC per capita in PPS in a given year (thresholds: 0.8; 0.6; 0.4 of the maximum value in a given year). The following formula was used to calculate entropy:

$$H(X) = -\sum p(x) \ln (p(x)) \tag{6}$$

where H(X) denotes the entropy of variable X, and p(x) denotes the probability of occurrence of value x.

Shannon entropy has the following features:

1. It takes a non-negative value.
2. It takes the value 0 when there is no differentiation (the variable takes one value, all countries are in one group).
3. The entropy index takes the highest value (1.386). The size of each group is equal (7 countries each).
4. The higher entropy index is due to the greater variety of categories that the variable adopts and the frequency of their occurrence in relation to all observations.

3. Research results

The analysis of β-convergence enables us to answer the question - whether the initially poorer countries experience a higher rate of AIC growth compared to the initially richer countries, which in the long run should have the effect of closing the gap between them. The β-convergence of the 27 EU countries and the UK over the period studied is depicted in Figure 2.

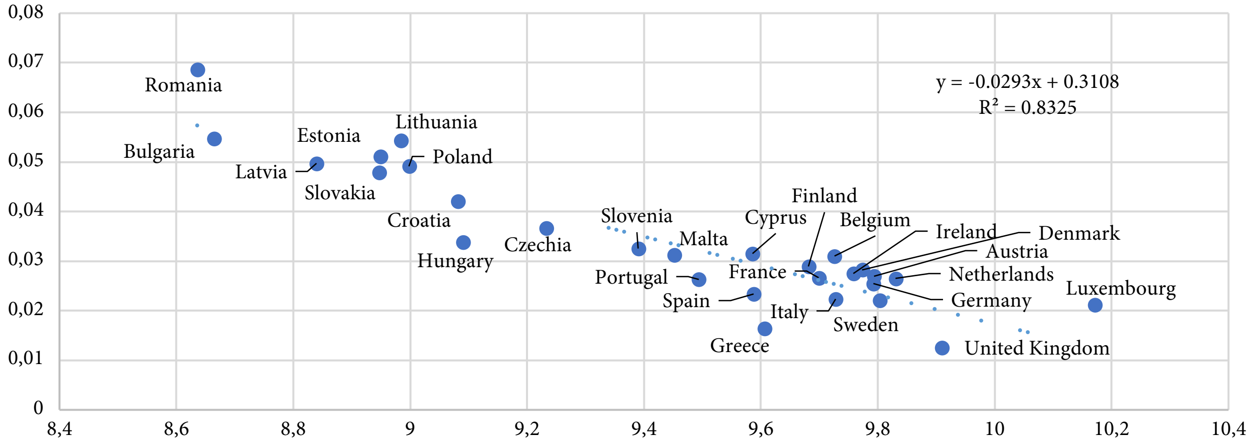

Figure 2. Beta (β) convergence of European Union (EU28) countries 2004–2023.
Source: own elaboration.

The results of the study indicate the existence of β-type convergence, meaning that less developed countries show a faster rate of growth in real individual consumption per capita than more developed countries. The evaluation of the parameter α1 in the econometric model is negative (-0.0293) and statistically significant. The dispersion of points representing individual countries is not large, the coefficient of determination is 0.8325, which means that the natural logarithm of the average AIC growth rate is 83% explained by the initial state (the AIC value in 2004). The speed (rate) of convergence coefficient β, which informs what percentage of the distance to the long-run equilibrium state the economy covers in one period, was 4.3% and the half-life index was 16.2. This implies that, if countries approach equilibrium at a rate of 4.3% per year, it will take more than 16 years to halve the distance separating them from a common hypothetical long-run equilibrium state.

The analysis of sigma convergence makes it possible to determine whether the differentiation of economies in terms of AICs is decreasing over time, i.e. whether the distribution of consumption is becoming more even. The σ convergence of the EU member states (and the UK) in the years under study is presented in Figures 3 and 4.

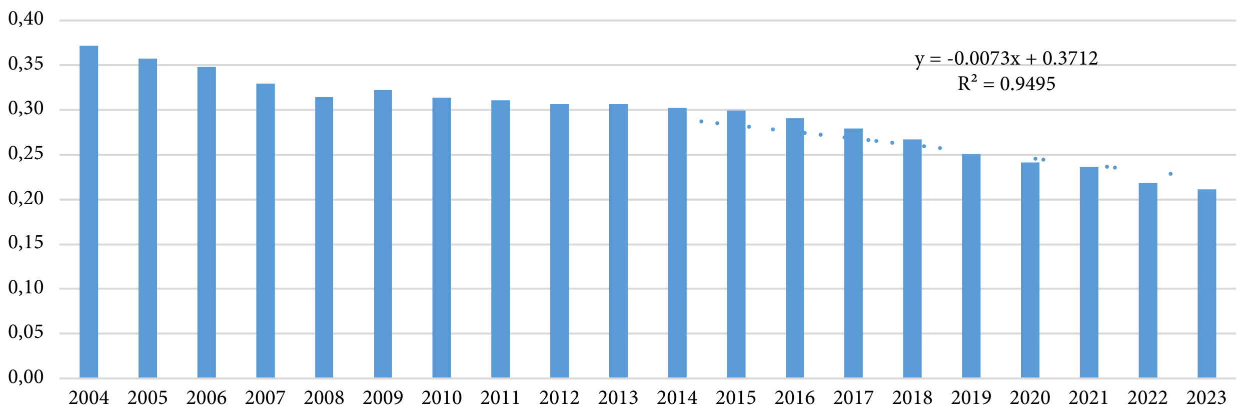

Figure 3. Sigma (σ) convergence of European Union (EU28) countries in 2004-2023 (coefficient of variation).
Source: own elaboration.

The analysis of sigma convergence performed on the basis of coefficients of variation and standard deviations of logarithms of the variable indicates the occurrence of a decrease in the diversity of the AIC level. Negative values of parameters and a high value of the coefficient of determination indicate the occurrence of sigma convergence in the European Union area in the years 2004–2023. The varying intensity of this process is also noticeable. Three periods can be distinguished: 2004–2008, with an apparent decrease in the AIC coefficient of variation (from 0.37 to 0.31); 2008–2015, with a decrease in convergence (coefficient of variation oscillating around 0.3); and 2015–2023, with a renewed increase in convergence (decrease in coefficient of variation to 0.21). The situation is similar with the standard deviation of the AIC logarithms: the periods of increased decline are 2004–2008 and 2015–2023.

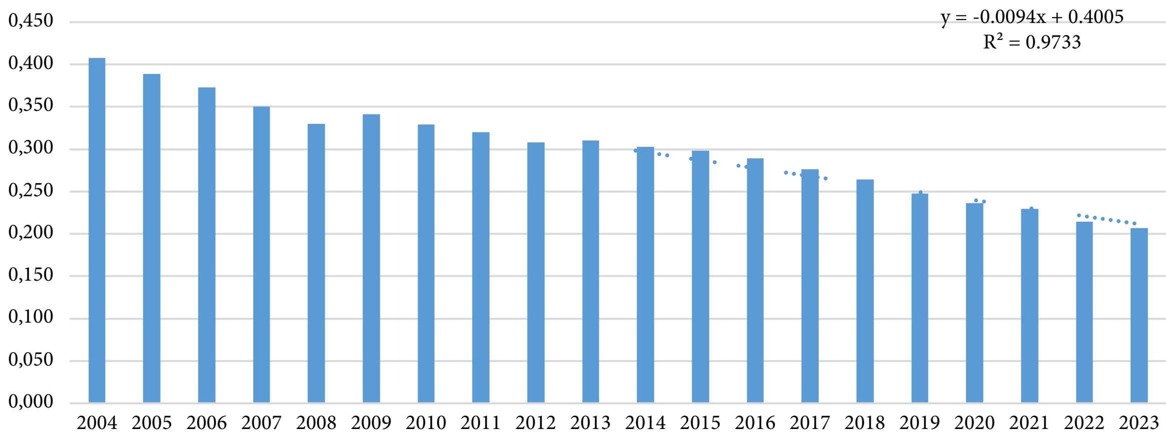

Figure 4. Sigma (σ) convergence of European Union (EU28) countries in 2004-2023 (standard deviation of logarithms).
Source: own elaboration.

Subsequently, the Shannon entropy index was used to assess the disparity in the development of EU member states, identifying those economies that have managed to improve their position to the greatest extent in terms of the measure of social development analysed. Table 2 contains information on the change in the value of the Shannon entropy index between 2004 and 2023 and the number of countries assigned to each group according to the results obtained.

Table 2. Shannon entropy index and number of countries in the group.

Rok	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Entropia	1.18	1.18	1.18	1.15	1.19	1.18	1.19	1.20	1.18	1.18	1.16	1.16	1.18	1.18	1.16	1.03	0.95	1.02	0.95	0.82
Grupa 4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Grupa 3	11	11	11	13	12	12	12	11	11	11	10	10	11	11	11	12	12	11	12	12
Grupa 2	6	6	6	5	7	6	7	7	10	10	12	12	10	10	11	13	14	14	14	15
Grupa 1	10	10	10	9	8	9	8	9	6	6	5	5	6	6	5	2	1	2	1	0

Source: own elaboration.

The entropy index was slightly different from its highest value of 1.386 until 2018. Such high entropy rates indicate very large discrepancies between EU countries due to actual individual consumption (dispersion of countries between different groups). We can only observe a notable decline in its value to 0.82 in 2023 over the last five years. If we look at the membership of countries in the different groups, we find an explanation for the relatively constant value of the entropy index between 2004 and 2018 (with sigma convergence taking place during this period - especially between 2004 and 2008).

In all analysed years, Luxembourg is included in group four as the only country, the undisputed leader. Group three in 2023 includes 12 countries: Belgium, Denmark, Germany, Ireland, France, Italy, Cyprus, the Netherlands, Austria, Finland, Sweden and the UK. The biggest changes occurred in terms of countries' membership of Groups 1 and 2, with the largest changes observed in countries with the lowest levels of AIC. Especially in the early period, a gradual outflow of countries from group one to group two is observed. Bulgaria was the last to leave group one. Table 3 compares the AIC of individual countries in relation to the ranking leader and their affiliation to groups in the first and last year of the period under review.

Table 3. Country's AIC share compared to leader and group membership, (share in %; change in pp.).

Countries	Share in 2004	Group	Share in 2023	Group	Change 2004-2023
Belgium	64	3	77	3	13
Bulgaria	22	1	42	2	20
Czechia	39	1	52	2	13
Denmark	67	3	77	3	10
Germany	68	3	74	3	6
Estonia	29	1	52	2	22
Ireland	66	3	75	3	8
Greece	57	2	52	2	-5
Spain	56	2	58	2	2
France	62	3	69	3	7
Croatia	34	1	50	2	16
Italy	64	3	66	3	1
Cyprus	56	2	68	3	12
Latvia	26	1	45	2	19
Lithuania	31	1	57	2	27
Luxembourg	100	4	100	4	0
Hungary	34	1	43	2	9
Malta	49	2	59	2	10
Netherlands	71	3	79	3	8
Austria	69	3	76	3	8
Poland	31	1	53	2	22
Portugal	51	2	56	2	5
Romania	22	1	53	2	31
Slovenia	46	2	57	2	11
Slovakia	29	1	49	2	19
Finland	61	3	71	3	10
Sweden	69	3	70	3	1
UK	77	3	65	3	-12

Source: own elaboration.

The last column of the table indicates the relative change in the country's AIC compared to the leader (Luxembourg). The largest change is observed in the following countries: Romania, Lithuania, Poland, Estonia and Bulgaria, Latvia, Slovakia. These are the countries with the lowest AIC in 2004, confirming the existence of convergence (Figure 2). Even in this group of countries, a distinction is made between faster and slower convergence - the first four countries mentioned are above the regression function, the last three are below the graph of the function. For the other "new members" of the EU, a change in the relative value of the AIC from 0.09 (Hungary) to 0.16 (Croatia) was observed (Table 3). Almost all of these countries (except Cyprus) have lower AIC growth rates than those derived from the regression equation (Figure 2). In particular, Hungary's AIC growth rate is surprisingly low.

Among the "old members" of the EU, the greatest change in the relative value of the AIC was observed in Belgium, Denmark, Finland, i.e. countries that had relatively low AIC values in 2004. Another group of countries with a slightly lower rate of convergence (an increase in relative value of around 0.06-0.08) are Germany, Ireland, France, the Netherlands and Austria. Countries whose position relative to the leader due to the AIC changed very little are Portugal, Spain, Italy and Sweden. A negative change in the relative value was recorded for Greece and the United Kingdom (although in this case it is necessary to remember the forecasted AIC values from 2020). In the case of Southern European countries as well as Sweden and the United Kingdom, a position below the convergence function is observed (Figure 2).

4. Discussion

The authors' main intention was to verify the existence of social convergence between EU member states (including the UK) between 2004 and 2023. Real social convergence is understood as an equalisation of the population's standard of living (material well-being). Real individual consumption in euro per capita at purchasing power parity - AIC per capita in PPS - was used as the variable informing the level of social development. The study uses different approaches to measuring the AIC convergence of EU countries in the years 2004-2023 - beta convergence, sigma convergence and the Shannon entropy index. Although these are, in a sense, complementary methods, their combined use allows for a comprehensive assessment of convergence. The analysis shows:

1. A statistically significant beta convergence was observed. Evaluation of the α_1 parameter (-0.0293) indicated a convergence rate coefficient of 4.3% and a half-life index of 16.2. It takes more than 16 years to halve the distance separating them from a common hypothetical long-run equilibrium state. This shows that the process of social convergence is a long-term phenomenon.
2. The periods in which an increased intensity of the AIC sigma convergence process was observed were 2004-2008 and 2015-2023. During the crisis and post-crisis years of 2008-2015, convergence occurred at a slower pace. Meanwhile, the negative impact of the phenomena of recent years (the pandemic and the war in Ukraine) on the convergence process has not been observed. This may be due to a short time frame and insufficient data, because in the social sphere, a longer period makes it possible to identify certain trends. In addition, our study considers the indicator of actual individual consumption per capita, which expresses the value of goods and services actually consumed by households and can be financed both from household's disposable income and financed by the state. It is therefore possible that during the crises (health and military) the state's participation in household expenditure increased to such an extent that their overall consumption expenditure did not fall, or even increased. The question of a relatively constant propensity to consume, i.e. the desire to maintain consumption at the level of previous periods and to finance it with savings, is also not insignificant. A more accurate diagnosis of this situation is possible on the basis of future analyses.
3. The highest growth rate of the AIC index is visible for countries that had the lowest real individual consumption indicators in 2004. Although the higher the AIC values observed in 2004, the lower the AIC growth rate was on average (which is in line with the idea of convergence), significant deviations can also be observed (e.g. Hungary as a country with a much lower convergence rate than that implied by the AIC in 2004, or Belgium as a country with a much higher convergence rate).

In summary, there has been a convergence in the living standards of population in the EU (and UK) countries across the 28 countries studied throughout the 2004-2023 period. The speed of convergence depends on the initial divergence in the level of development across EU countries. In general, for countries with a higher level of welfare in the starting year, the rate of convergence was slightly lower, while stronger processes took place among countries starting from a lower level of social development. These processes are consistent with both sigma convergence and beta convergence. Nevertheless, deviations from the general beta pattern of convergence were also noted. For example, Hungary, whose AIC in 2004 was only 61.6% of the EU average, increased this indicator to 67% in 2023 (5.4 pp.), indicating a low rate of convergence. Belgium, on the other hand, started with a consumption level more than 16% higher than the EU average, maintaining a high pace throughout the period under review. By the way, the high rate of real convergence of per capita consumption in countries such as Romania, Lithuania, Bulgaria, Estonia or Poland ("new" member states) may result from the significant scale of emigration and the decline in the number of inhabitants, characteristic of this group of countries, especially in Central and Eastern Europe. In addition, the number of deaths in relation to births also increased significantly in some of these countries after the pandemic outbreak. These factors meant that the growth rate of AIC per capita in these countries was significantly higher than the growth rate of consumption in absolute terms.

Conclusions

The importance of this study is that it provides important information on the degree of social convergence between European Union member states. There is no doubt that all EU countries have benefited directly and indirectly from EU accession, as revealed by the analysis of real social convergence carried out, but these benefits must be assessed on the basis of the specific characteristics of the individual regions or countries of the Community. For example, despite the relative similarity between the "new" EU countries, there are different social and economic development models, and the factors determining this development are also different. Nor is there a single, optimal model of development and convergence that can be applied to the entire study population. Other researchers also come to similar conclusions (Landesmann& Székely, 2021). Given the noted deviations from the general trend, further analysis should be conducted at the level of a group of countries (e.g. Central and Eastern European countries or "new" members of the grouping) or even individual countries.

The applied aim of the study was to assess the extent of the reduction in the gap in individual consumption (well-being and quality of life). This can help guide future economic policies and measures to further reduce the gap. In addition, the authors distinguished the countries that succeeded most in improving their position in terms of the measure of social development analysed in relation to the other EU countries. However, the question remains open as to whether these results are actually translated into the well-being and quality of life of their citizens, i.e. whether success at the level of EU member states is accompanied by sustainable regional development at the national level. This question requires further in-depth analysis.

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Determinants of the Acceptance of RPA Technology in a Medical Facility

Lukasz Sulkowski [1], Paula Pyplacz [2], Janusz Sasak [3,*]

[1] WSB University, Dabrowa Gornicza, Poland
ORCID: 0000-0002-1248-2743
e-mail: lsulkowski@wsb.edu.pl

[2] Czestochowa University of Technology, Czestochowa, Poland
ORCID: 0000-0003-1821-8094
e-mail: paula.pyplacz@pcz.pl

[3] Jagiellonian University, Krakow, Poland
ORCID: 0000-0003-0989-3987
e-mail: janusz.sasak@uj.edu.pl

* Corresponding author: Janusz Sasak, janusz.sasak@uj.edu.pl

Abstract

This article explores the implementation and acceptance of Robotic Process Automation (RPA) technology at the Hospital of Pulmonary Diseases in Olsztyn, Poland. With the healthcare sector increasingly under pressure to enhance efficiency while maintaining high-quality patient care, RPA provides a promising avenue for process optimization. Understanding the factors that affect the acceptance and successful implementation of this technology is critical for organizations seeking to leverage its full potential. The main purpose of this paper is to investigate the factors influencing the acceptance of RPA technology in a medical facility, using the MARPA technology acceptance model. The study aims to identify organizational determinants related to personnel, tasks, and structure that impact the success of RPA adoption. The research employs the MARPA technology acceptance model as a framework for analysing organizational factors. The study focuses on qualitative and quantitative data from the Hospital of Pulmonary Diseases to assess the interplay between change management, staff support, and the alignment of RPA technology with specific organizational needs. The findings reveal that the successful acceptance of RPA technology in medical facilities hinges on effective change management, robust staff support, and the customization of RPA solutions to meet the unique requirements of the organization. Employees buy-in and adaptability to technological change were identified as critical components of success. This paper contributes to the literature on technology acceptance in healthcare by applying and validating the MARPA model in a real-world setting. It highlights the interplay between organizational dynamics and technology adoption, offering a nuanced understanding of the factors influencing RPA implementation. The research underscores the importance of strategic change management and workforce engagement when introducing RPA in healthcare settings. It provides actionable insights for managers and decision-makers, emphasizing the need for tailored technology solutions and structured support systems to ensure successful adoption and integration of RPA into organizational processes.

Key words

Robotic Process Automation, technology acceptance, model MARPA management, healthcare units.

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Introduction

In recent years, robotic process automation (RPA) technology has become popular in the market. RPA involves the use of specialized software that mimics human workflows. Modern software robots create intelligent and friendly digital workforces, capable of performing tasks that were previously performed only by humans thanks to new functions and integration with user interfaces (Pypłacz & Sasak, 2022). According to statistics, expenditures on RPA have been gradually increasing since 2020. Projections indicate that the market size will grow from $1.23 billion in 2020 to $13.39 billion by 2030. Research also presents even more optimistic forecasts, suggesting that the RPA market, valued at $2.3 billion by 2023, will reach $66 billion by 2032, with a Compound Annual Growth Rate (CAGR) of 39.9% (Market Research Report, 2023).

Many organizations and researchers view RPA as an emerging technology that enhances productivity and operational flexibility (Fernandez, Aman, 2018), improves quality (Kokina & Blanchette, 2019), and reduces costs (Hallikainen et al., 2018) and risk (Burgess, 2018; Syed et al., 2020). By integrating RPA into management structures, it is possible to develop new business models, create new processes (including those that engage customers and/or the environment in collaboration or are fuelled by data), and modify existing ones.

The implementation of RPA technology is regarded as a comprehensive undertaking that encompasses the entire organization. As noted by Lacity et al. (2016), it is primarily a business initiative with an IT component. Therefore, it should be treated as an organizational change rather than merely software implementation (Pypłacz & Zukovskis, 2023). RPA represents non-traditional automation, which does not require integration at the database or infrastructure level. It can operate non-invasively within applications, leveraging existing infrastructure, and functions as an assistant to the computer operator.

Today, there are very few organizations that do not use IT tools or IT solutions in a broad sense. There are many solutions that support many different areas of business. Simultaneously, the conventional technological barrier of inadequate IT skills is gradually diminishing. Workers are becoming more adept at using technological tools and solutions. In order for new technologies to be implemented in businesses efficiently, they need to be embraced and integrated into workers' daily tasks. Since innovation is being included into employees' day by day lives from the starting, it is getting to be progressively critical to comprehend the variables that impact employees' acknowledgment or dismissal of innovation.

This ponder looks into the organizational components that influence a therapeutic facility's selection of RPA innovation. The RPA Innovation Acknowledgment Show – MARPA given the system for the develops relating to individuals, assignments, structure, and innovation acknowledgment (Pypłacz, 2024).

1. Literature review and hypotheses development

1.1 Robotics Process Automation

To preserve competitiveness, organizations endeavour to progress the proficiency of their operations, counting through the overhaul and administration of trade forms. Data innovation plays a key part in supporting these changes (Al-Gasawneh et al., 2021). Among more than 900 respondents overviewed within the Forbes Insights/KPMG report (KPMG Transformation Study, 2017), 93.0% expressed that they are arranging, within the handle of, or have fair completed a trade transformation. One of the key components of this change is prepare computerization. Agreeing to investigate by Olszynka et al. (2022), robotization most commonly includes detailing (68.0%), data collection from items utilized by clients (55.0%), and frame filling (49.0%). The most benefits recognized incorporate a decrease in prepare term (89.0%) and the disposal of blunders and exclusions (78.0%).

The term RPA combines robotics, which refers to software robots (software agents) that act like employees in system interactions, and process automation (Hallikainen et al., 2018; Syed et al., 2020; Kajrunajtys & Kajrunajtys, 2022). Robotic Process Automation is a specific form of automation aimed at transforming processes by partially or entirely replacing traditional solutions with digital ones. It particularly involves redirecting repetitive and high-volume tasks performed by humans to software robots (Lacity & Willcocks, 2015; Lacity et al., 2015; Bruno et al., 2017; Fernandez & Aman, 2018;

Cohen, Rozario, 2019; Kokina & Blanchette, 2019), thereby relieving employees of tedious, routine tasks and allowing them more space for creative work (Lacity & Willcocks, 2015; Agostinelli et al., 2019; Berruti et al., 2017; Cewe et al., 2018). RPA does not involve physical robots but software robots whose typical tasks include migrating large volumes of data between different systems with comparison and validation, automating email distribution to a large number of users, data acquisition from various sources, data updating, and handling different tasks based on operations in IT systems (Marciniak & Stanisławski, 2021a). This technology can only be applied to business processes with clearly defined rules and business logic. It primarily involves interacting with IT system interfaces by replicating the steps taken by employees to navigate through the entire business process (Geyer-Klingeberg et al., 2018).

The concept of RPA innovation isn't unequivocally characterized, as famous by Sobczak (2018), Syed et al. (2020), Gao et al. (2021), Marciniak & Stanisławski (2021b), Ghouse & Sipos (2022), and da Silva Costa et al. (2022). In the literature, various authors present different approaches, concepts, and literature reviews in this area, attempting to establish some framework for this solution. Definitions frequently highlight the aspects of a "computer program" and the "replacement or imitation of human work". Less frequently, definitions of RPA include terms related to automation and descriptions of tasks performed within the technology.

For the purposes of this consider, RPA is characterized as a innovation based on progressed computer program apparatuses, computer equipment, and amassed information, empowering the impersonation of human behaviour in intuitive with computer applications. It is especially reasonable for dreary errands, whether including whole forms or particular parts thereof. RPA on a very basic level modifies work organization by presenting program robots into forms that reenact human activities in tedious exercises (Pypłacz, 2024).

2.1 RPA in Healthcare Units

As of now, clinics confront various challenges emerging from expanding understanding desires, budget imperatives, and the quickly advancing mechanical and lawful environment. In look of arrangements, there's a developing centre on prepare mechanization, which empowers more proficient administration of therapeutic units, moves forward the quality of administrations given, and upgrades understanding security (Czerwińska, 2015). Automation in the healthcare sector encompasses the management of electronic documentation for both administrative and medical processes, data exchange with institutions that fund and supervise healthcare facilities, communication and information exchange with patients, and the implementation of electronic tools that support diagnostics and therapy. It is assessed that in Poland, handle computerization is still in its early stages of improvement (Janik, 2024). This computerization regularly centres on restorative and demonstrative strategies, frequently ignoring authoritative regions. As a result, robotization forms are not conducted comprehensively and as a rule address person zones, driving to a need of coordination and the nonappearance of an coordinates framework to bolster healing centre forms (Szczerbak & Szczerbak, 2024). This fragmented approach to automation, known as "island automation," prevents healthcare units from fully realizing the benefits of process automation. The low awareness of the need for comprehensive solutions is evidenced by the relatively small proportion of hospitals – only 25% – that employ individuals responsible for process optimization and improvement (Process Automation in Healthcare). This situation further indicates a limited awareness of modern management methods and tools among managers.

Literature sources indicate that the most common areas of automation implementation in healthcare involve medication and medical supply management, where vending machines are used for internal purposes. Computerization in this zone covers two fundamental perspectives: specialized mechanization, which includes the utilize of gadgets for apportioning and collecting solutions, and information stream administration, which controls and confirms the exactness of apportioned drugs. The moment zone of computerization is the bolster of demonstrative forms and clinical case investigation, frequently utilizing arrangements based on fake insights and machine learning (Denisiewicz, 2024). In Polish healthcare facilities, this type of automation is relatively rare due to the specificity and high costs associated with AI technologies. Nonetheless, chatbots have found wide application (Taulli, 2020; Chakrabortti et al., 2020), particularly in patient registration systems and for collecting health-related data (Dryl, 2024). Although these technologies are among the most commonly used, they are not always recognized as process automation technologies, mainly because chatbot systems are often seen as autonomous IT systems rather than integral automation solutions. In the healthcare sector, processes are being automated across all areas of operation, including the administrative domain, where several fundamental technologies are applied. Most commonly, components implanted in healing centre data frameworks are utilized, whereas committed arrangements or RPA-class apparatuses are once in a while utilized (Skoczylas, 2023). The application of RPA innovation is basically watched in back-office offices, especially in regulatory and budgetary forms (Ortiz& Costa, 2020; Gotthardt et al., 2020). An analysis of IT technology use in Polish hospitals revealed that the adoption of RPA technology is very limited. Typically, RPA technology creates a so-called "virtual back-office," where processes are executed without direct human involvement, delivering high efficiency (Willcocks et al., 2017). It is important to note that the range of processes suitable for such improvements is limited. These are generally systematic processes with a high degree of repetition, schematically performed within existing IT systems via the user interface (Penttinen et al., 2018). Inquire about conducted by the Clean Healing centre Alliance shows (Robotyzacja procesów w Ochronie Zdrowia, 2022) that there's critical potential for the execution of RPA innovation in healing centres. This would permit for considerable decreases in information preparing mistakes. The key to effective process automation lies within the integration of these mechanical arrangements into a bound together framework that envelops both administrative and therapeutic forms, in this manner empowering the complete realization of the benefits of mechanization.

Despite the growing interest in process automation across various sectors, the scientific literature still lacks a sufficient number of empirical and theoretical studies that provide a detailed analysis of the application of Robotic Process Automation (RPA) in the specific context of hospitals and medical institutions.

An analysis of articles available in the Scopus database confirms that although RPA technology is increasingly recognized as a tool for improving efficiency and reducing costs, the majority of publications focus on its applications in financial, logistical, or administrative sectors (c.f. Pypłacz, 2023). Publications addressing healthcare are considerably less frequent, and their content is dominated by general theoretical discussions, with limited focus on practical implementations or the specific challenges faced by hospitals.

To provide readers with an overview of the state of scientific publications in this area, a brief bibliometric analysis was conducted based on the Scopus and Web of Science (WoS) databases. Due to the similarity of results obtained from WoS and the exploratory nature of this element, the article presents detailed findings based on data from the Scopus database (as of November 25, 2024). Between 2000 and 2024, the Scopus database identifies 306 publications retrieved using the query (TITLE-ABS-KEY (rpa AND technology) OR TITLE-ABS-KEY (software AND robot) AND TITLE-ABS-KEY (medicine) OR TITLE-ABS-KEY (health AND service) OR TITLE-ABS-KEY (hospital) AND NOT TITLE-ABS-KEY (robot AND assisted) AND NOT TITLE-ABS-KEY (hardware) AND PUBYEAR > 1999 AND PUBYEAR < 2025 AND (EXCLUDE (SUBJAREA , "MATH") OR EXCLUDE (SUBJAREA, "BIOC") OR EXCLUDE (SUBJAREA , "PHYS") OR EXCLUDE (SUBJAREA , "MATE") OR EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "ENER") OR EXCLUDE (SUBJAREA , "AGRI") OR EXCLUDE (SUBJAREA , "EART"). This query was the result of iterative testing with various datasets. Following abstract analysis, several exclusions were made, as many articles addressed the use of hardware robots as surgical or procedural assistants, rather than software-based automation.

As illustrated in Figure 1, an increase in the number of publications has been observed only since 2012, with approximately a dozen publications per year. Notably, 2021 saw a marked rise in publication volume, likely linked to the COVID-19 pandemic and the increased focus on automating activities within healthcare institutions during this period.

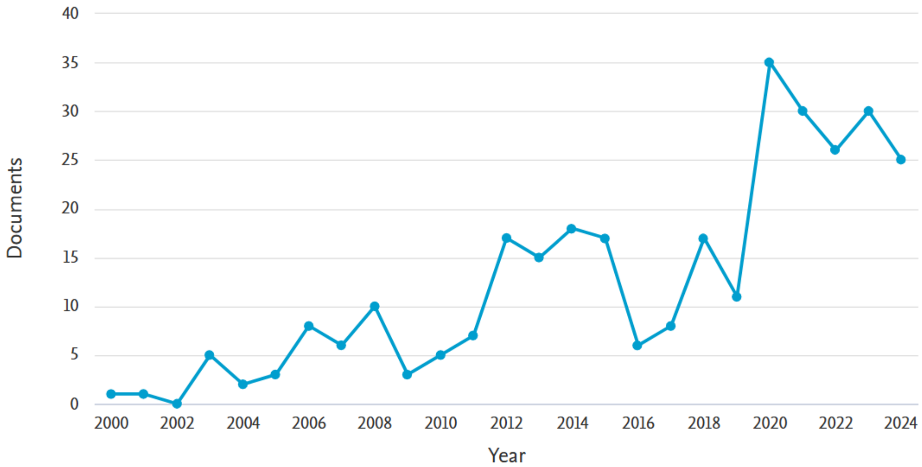

Figure 1. Number of publications by year in the Scopus database on the use of RPA technology in healthcare institutions.
Source: Own study, as of November 25, 2024.

It is worth noting (Figure 2) that the majority of the analysed publications focus on areas such as computer science (32.4%), engineering (24.7%), decision sciences (5.0%), social sciences (5.0%), and business, management, and accounting (2.8%). The remaining publications fall within the medical field and, to a large extent, analyse medical aspects in their content.

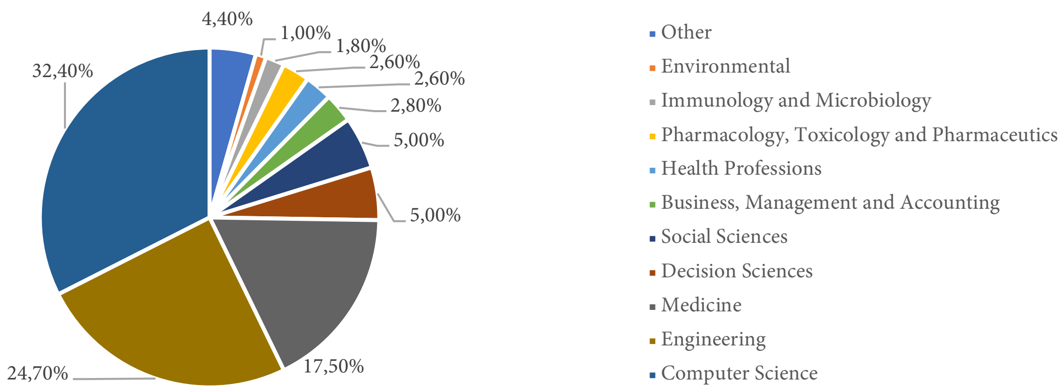

Figure 2. Publications in the Scopus database on the use of RPA technology in healthcare institutions by research areas.
Source: Own study, as of November 25, 2024.

An analysis of abstracts and selected content reveals a lack of detailed studies on the impact of RPA on organizational workflows in medical institutions, such as changes in employee roles, interpersonal relationships in automated environments, effects on the quality of healthcare, or shifts in organizational culture. Additionally, the literature lacks case studies documenting the detailed implementation of RPA in hospitals, which could serve as a valuable source of practical knowledge for other institutions considering process automation. Furthermore, there are few studies addressing the long-term effects of RPA adoption in healthcare facilities, such as its impact on cost reduction, efficiency improvement, or the satisfaction levels of both patients and employees.

The analysis of keywords presented in the word map (Figure 3) illustrates the key terms associated with the RPA topic and their frequency in the reviewed publications from the Scopus database. A diversity of terms is evident, reflecting the wide range of applications and connections to various disciplines, including robotics (76 occurrences), humans (43), artificial intelligence (31), and healthcare (29).

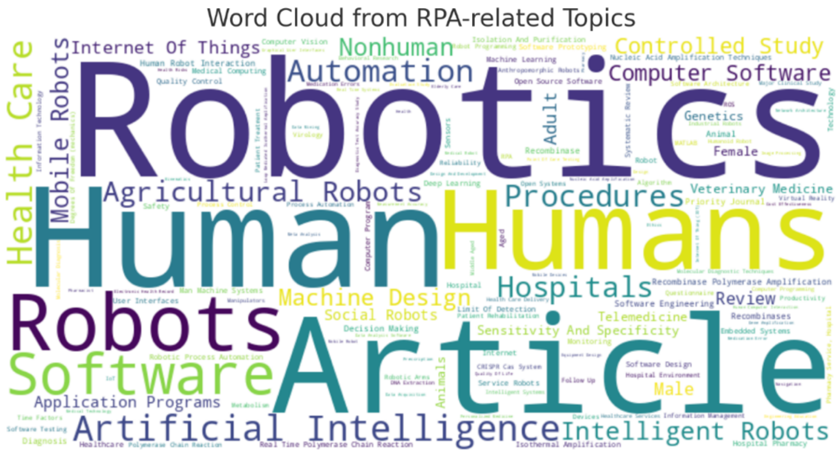

Figure 3. Keyword map on the use of RPA technology in healthcare institutions based on publications from the Scopus database.
Source: Own study, as of November 25, 2024.

From the perspective of management and quality sciences, a relatively small proportion of publications is directly related to this area. Although RPA technology is applied across various fields such as computer science, engineering, and social sciences, its exploration in the context of process management, quality optimization, or organizational transformation in healthcare institutions is marginal. This situation highlights a research gap that calls for more in-depth analyses, particularly concerning the impact of automation on management efficiency, organizational structures, and the operational culture of institutions such as hospitals.

1.2 Acceptance of RPA Technology in Business Process Automation

Numerous changes in organizations are driven by mechanical changes, counting the usage of program robots. Leavitt's (1964) demonstrate serves as a apparatus for clarifying the concept of organizational alter, which envelops activities that organizations routinely experience. In spite of the fact that the show does not diagram a particular way for alter, it permits for a comprehensive investigation of the alter handle. Changes occur in each area represented in the model and, importantly, affect other organizational elements. The model's creator presents it based on components in which individual variables hold specific significance while simultaneously considering other factors. These components include structural, technological, and social approaches. The common goal of these three components is to enhance tasks, contributing to the implementation of solutions, innovations, and changes. The relationship between structure and the people area is very strong and can have both positive and negative effects, particularly concerning employee behaviour and efficiency. Any modification of the structure leads to changes in employee behaviour and necessitates adjustments in competencies. Integrating software robots into the organizational structure alters the scope of employee responsibilities, affecting the number of tasks, hierarchy, and the range of control. From another perspective, the development of new technologies and the evolution towards digitalization contribute to changing the employee profile, which consequently necessitates organizational changes, such as the creation of new structures or internal adjustments within departments or divisions. Employees are assigned new roles and responsibilities within the newly established structure.

The techno-structural approach to alter is based on improving productivity by adjusting certain viewpoints of both structure and innovation. Cases of techno-structural approaches to alter incorporate work extension and enhancement programs, which point to supply workers with more noteworthy work assortment, expanded duty for their work, and the next sense of engagement. This approach seeks to improve organizational efficiency by altering the work environment, which should, in turn, lead to increased employee productivity. Work automation and digitalization respond to the need for departmental reorganization, cost reduction, and productivity enhancement. It is also essential to consider the humanistic objectives of job enrichment, including task complexity as a source of motivation. These changes naturally lead to further consequences. Structural modifications trigger changes in tasks that are directly linked to employees. The introduction of new departments, new management levels, and new employee competencies result in changes to the tasks performed by employees. Auxiliary changes too affect workflow and prepare organization. Changes in the organizational structure affect workflow and the organization of processes. Every change in the course of a process forces employees to adapt to new conditions, which requires training to acquire new skills, gain experience, and share knowledge.

It is important to consider the relationship between technology, tasks, and people (Jędrzejczyk, 2021). Changes in technology lead to alterations in tasks and activities, but it is the employees who must adapt to these changes by collaborating with technology or reducing manual tasks. Successful adaptation requires a well-designed training program. Technological changes may sometimes necessitate hiring new employees, which not only affects the organization of work but also leads to the emergence of new communication channels and methods, as well as new formal and informal personal relationships. It should also be noted that the relationship between technology and people is bidirectional. To a large extent, the skills and knowledge of the organization's employees determine the level of technology that is used and can be implemented. If employees are not adequately prepared to use the new technology, its utilization will be limited, rendering the implementation ineffective. When implementing new technologies, there is a high risk that employees will reject the introduced solutions because they do not understand or are unfamiliar with them. Technology acceptance is a complex process in which users adopt and adapt new technologies into their daily use. This process is influenced by psychological, social, and cultural factors that either support an individual's or group's readiness to accept and use a given technology or hinder its implementation. According to technology acceptance models (TAM – Technology Acceptance Model, UTAUT – Unified Theory of Acceptance and Use of Technology), factors influencing technology acceptance include:

- Perceived usefulness: the subjective belief that using RPA technology will improve job performance and increase efficiency (Davis, 1989).
- Perceived ease of use: the extent to which an individual believes that using RPA technology will be effortless, relating to beliefs about the challenges encountered while using RPA (Davis, 1986; 1989).
- Behavioural intention to use: defined as the belief in the ability to perform an action using RPA (Nahotko, 2014).

Based on the analysis of the literature, a research model was proposed. This model is presented in Figure 4.

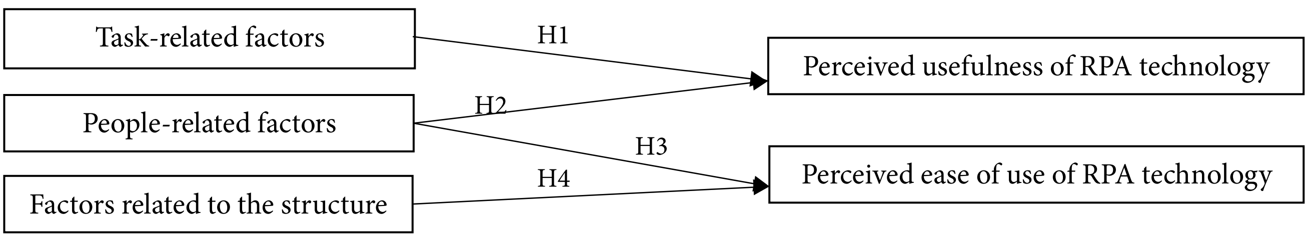

Figure 4. Hypotheses.
Source: own study.

Hypotheses 1: Task-related factors influence the perceived usefulness of RPA technology in automating the hospital's business processes. Tasks were defined according to Leavitt's model and the technology acceptance models TAM and UTAUT, as follows:

- Willingness to "interact" with RPA / "play with RPA": The user's intrinsic motivation to explore RPA technology and the desire to create additional scenarios (RPA playfulness). It reflects the level of cognitive spontaneity in interactions with software robots (Webster & Martocchio, 1992, p. 204).
- Result demonstrability: The degree to which an individual believes that the outcomes of using the system are tangible, observable, and communicable (Moore & Benbasat, 1991).

Hypotheses 2: People-related factors influence the perceived usefulness of RPA technology in automating the hospital's business processes.

Hypotheses 3: People-related factors influence the perceived ease of use of RPA technology in automating hospital business processes. Referring to hypotheses 2 and 3, the people domain, in accordance with Leavitt's model and technology acceptance models TAM and UTAUT, has been defined as follows:

- Subjective norm / social influence: The extent to which the user perceives that important individuals believe they should or should not use RPA technology (related to behaviour and/or decision-making) (Fishbein & Ajzen, 1975; Ajzen, 1991; Venkatesh & Davis, 2000).
- User engagement in the functioning of RPA within the organization: This factor is always variable, progressing through the cycle of change acceptance and then through the life cycle of the technology in a given job position.
- Trust in robots: Two main aspects of trust in technology can be distinguished (Ejdys, 2017): those related to the perceived features of the technology, such as its functionalities, and the declared willingness to rely on the technology, stemming from its inherent characteristics. Trust is analysed from the perspectives of reliability and the potential for risk.
- Computer literacy: The extent to which an individual believes they can perform a specific task using computer technology (Compeau & Higgins, 1995a, 1995b).

Hypotheses 4: Structure-related factors influence the perceived ease of use of RPA technology in automating the hospital's business processes. The structure domain is defined according to Leavitt's model and the technology acceptance models TAM and UTAUT as:

- Job relevance / fit to the job: The extent to which the user believes that RPA technology is applicable to their work (Venkatesh & Davis, 2000).
- Availability of external and internal support: The degree to which an individual believes that organizational, technical, and human resources are available to support RPA solutions within the organization (Venkatesh et al., 2003).

2. Methodology

For the purposes of this study, the technology acceptance model developed in 2024 (Pypłacz, 2024) was utilized. The model, designated by the acronym MARPA, was specifically designed for small and medium-sized enterprises, taking into account their unique characteristics, such as the absence of specialized departments, lack of expert programming staff, and limited resources. These criteria are also met in the hospital under study, as the automation involves small units where employees work directly with software robots, and the implementation of RPA technology was driven, among other reasons, by the lack of human resources for administrative tasks.

The MARPA model was published in 2024 as an innovative concept designed to support business process automation in SMEs. However, to date, there are no scientific publications or empirical studies demonstrating its practical application in other entities. The model identifies eight external variables categorized into three domains: people, tasks, and structure. These variables are described by detailed factors, as outlined below:

- Willingness to "interact" with RPA / "play with RPA," understood as:

- Perceiving work with software robots as enjoyable and entertaining.
- Freedom to perform tasks using new technologies.
- Absence of fear that software robots will take over jobs.

- Ability to present outcomes, understood as:
  - Ability to explain and present the goals and outcomes of software robots' work.
  - Understanding the results of software robots' tasks.
  - Ability to explain the benefits of using software robots.
- Subjective norm / social influence, understood as:
  - Perception of software robots by external stakeholders.
  - Perception of software robots by individuals directly associated with the employee.
  - Perception of software robots by supervisors.
- User engagement in the functioning of RPA within the organization, understood as:
  - Direct involvement in the implementation of robotic automation.
  - Direct involvement in testing software robots.
  - Familiarity with the assumptions and capabilities of robotic automation.
- Trust in robots, understood as:
  - Protection of privacy while working with software robots.
  - Trust in the resistance of software robots to manipulation.
  - Confidence in the accuracy of software robots' work results.
  - Trust that software robots' operations align with predefined assumptions.
- Proficiency in using computer technologies, understood as:
  - Ability to assist others with IT-related issues.
  - Capability to resolve unexpected IT-related problems.
  - High-level problem-solving skills related to IT system functionality.
- Work utility / fit to the job position, understood as:
  - Relevance of software robots in the job.
  - Necessity of using software robots for work.
  - Alignment of software robots with the employee’s work style.
- Availability of external and internal support, understood as:
  - Equipping the organization with resources necessary for software robots' usage.
  - Direct supervision by an individual knowledgeable about software robots.
  - Accessibility of support for resolving issues with software robots' operation.

2.1 Research design

The consider included 34 representatives of the Clinic of Aspiratory Maladies in Olsztyn, Poland. In June 2023, the healing centre propelled a pilot venture of understudy internships, amid which RPA innovation was executed over all zones of healing centre operations. The essential ponder was quantitative and conducted in July 2024, one year after the graduation of collaboration with computer program robots. Among the respondents were 9 regulatory staff individuals and 25 therapeutic staff (n=34), speaking to 100% of the people who have been working with computer program robots for the past year. Thus, all respondents are recognizable with RPA innovation.

The survey questions focused on the perception of individual factors related to people, tasks, and structure. The questions predominantly used an ordinal scale (7-point Likert scale), and individual items were derived from the previously introduced MARPA model. Due to the use of the MARPA model, which illustrates the relationships between the identified constructs, a quantitative approach through survey research was chosen. This choice was also driven by the need to analyse factors influencing the acceptance of RPA technology.

The investigate strategy utilized conventional inductive-deductive strategies and factual apparatuses, utilizing the STATISTICA 13 computer program. Expressive measurements, such as the middle (Mi) and mode (Mo), were utilized to display the comes about. Cronbach’s alpha coefficient was applied to assess the reliability of the measurement scales. The conducted analyses were performed according to the correlational model. Although the correlational model itself is not intended for causal interpretation, its elements allow for cautious derivation of such conclusions (Aczel & Sounderpandian, 2021). In structural models based on primary data, the significance of causal relationships is assumed to be based on correlational dependency. The proposed MARPA model concept shows such a relationship between variables. Therefore, the strength and direction of the relationship between variables were determined using Spearman's rank correlation coefficients, with significance set at $p < 0.01$, and the strength of the correlation assessed using Guilford's scale. This method was also applied because the obtained distribution could not be considered normal.

3. Results

All variables studied take values between 5 and 7 on the 7-point scale. The Mo and Mi values for most variables are at a similar level (Mi = 5, Mo = 7). Therefore, it can be concluded that all variables are quite important for the acceptance of RPA technology. The variables show moderate to high variability, indicating heterogeneity in the study population. Reliability analysis of the applied measurement scales using Cronbach's alpha coefficient demonstrated high internal consistency for the entire test ($\alpha = 0.91$) and satisfactory reliability for individual scales ($\alpha > 0.81$).

One of the assumptions of the tested MARPA model is based on the existence of a relationship between the perceived usefulness of RPA technology and task-related factors, as shown in Table 1.

Table 1. Spearman's rho correlation coefficient for the variable perceived usefulness of RPA technology.

		Willingness to "interact" with RPA / "playfulness with RPA"	**Result demonstrability**
Perceived usefulness	Correlation coefficient	0.772**	0.693**
	Significance (two-sided)	0.000	0.000

Note: ** Correlation significant at 0.01 (two-sided); n=34.
Source: elaborated by the authors.

For the variables related to the task domain and the perceived usefulness of RPA technology, the correlation was moderate and statistically significant at the level of $p < 0.01$ (Table 1). The detailed factors that proved significant were the freedom to perform tasks using new technologies and the absence of fear that software robots would take over jobs. The relationships between perceived usefulness and the willingness to "play" with RPA, as well as the ability to present results, are positive and show clear dependencies.

Another assumption of the tested MARPA model is based on the existence of a relationship between the perceived usefulness of RPA technology and the perceived ease of use of RPA technology and factors related to the people domain, as reflected in hypotheses 2 and 3. The results are presented in Table 2.

Table 2. Spearman's rho correlation coefficient for the variables perceived usefulness and perceived ease of use of RPA technology.

		Subjective norm / social influence	**User engagement in the functioning of RPA within the organization**	**Trust in robots**	**Computer Literacy**
Perceived usefulness	Correlation coefficient	0.698**	0.645**	0.793**	0.763**
	Significance (two-sided)	0.000	0.000	0.000	0.000
Perceived ease of use	Correlation coefficient	0.784**	0.826**	0.564**	0.719**
	Significance (two-sided)	0.000	0.000	0.000	0.000

Note: ** Correlation significant at 0.01 (two-sided); n=34.
Source: elaborated by the authors.

The data presented in Table 2 show that all correlations are significant at the level of $p < 0.01$. For perceived usefulness, the strongest relationships are exhibited by the factors: trust in software robots (0.79; $p < 0.01$) and computer literacy (0.76; $p < 0.01$). In the case of the perceived usefulness of RPA technology, the factor of user engagement in the functioning of RPA within the organization shows the strongest relationship (0.83; $p < 0.01$). The factors subjective norm / social influence and computer literacy also demonstrate a positive, significant relationship with the perceived ease of use of RPA technology (above 0.7; $p < 0.01$). On the other hand, trust in robots shows a moderate relationship with perceived ease of use (0.56; $p < 0.01$), which may be due to the high-risk level of tasks performed by robots. The specific task-related factors that proved significant include: the perception of software robots by supervisors, direct involvement in the implementation of robotic automation, familiarity with the assumptions and capabilities of robotic automation, protection of privacy while working with software robots, trust in the accuracy of software robots' work outcomes, trust that software robots operate in accordance with predefined assumptions, the ability to assist others with IT-related issues, the ability to resolve unexpected IT-related problems, and a high level of proficiency in solving IT system functionality issues. Consequently, employees still verify whether errors occur during the operation of software robots.

Therefore, it can be concluded that factors related to people, perceived usefulness of RPA technology, and perceived ease of use of RPA technology have a clear, positive relationship. The next assumption of the tested MARPA model is based on the existence of a relationship between the perceived ease of use of RPA technology and structure-related factors, as reflected in hypothesis 4, with results presented in Table 3.

Table 3. Spearman's rho correlation coefficient for the variable perceived ease of use of RPA technology.

		Job relevance / fit to the job	**Availability of external and internal support**
Perceived ease of use	Correlation coefficient	0.548**	0.572**
	Significance (two-sided)	0.000	0.000

Note: ** Correlation significant at 0.01 (two-sided); n=34.
Source: elaborated by the authors.

Structure-related factors, such as job relevance / fit to the job and the availability of external and internal support, as well as the perceived ease of use of RPA technology, have a significant positive relationship ($p < 0.01$), but in this case, the correlations are moderate. Therefore, the structure is the least associated with technology acceptance. The specific factors that proved significant include: the alignment of software robots with the work style, the organization's provision of resources necessary for using software robots, direct supervision by an individual knowledgeable about software robots, and the availability of contact with a person assisting in resolving issues with the operation of software robots. This may be due to the highly formalized organizational structure of the hospital and the fact that, in the discussed implementation, the individuals training the robots are continuously available on-site.

4. Discussion

The analysis conducted using Spearman's rho correlation coefficient showed that all correlations are significant, although they vary in strength. The obtained coefficient values ranged from $r = 0.55$ to $r = 0.82$ ($p < 0.001$), indicating moderate to strong relationships. Task-related variables essentially impact the seen convenience of RPA innovation. Seen convenience increments when representatives upgrade their abilities in clarifying and displaying the objectives and results of program robots, as understanding the impacts of robot work and the capacity to verbalize the benefits of working with program robots' progress. Purposefulness and understanding of the task are important for employees because when they comprehend the effects of robot work, they can demonstrate these to others and discuss them. Similar observations are presented by Wewerka & Reichert (2020), who highlight the importance of obtained outcomes and their measures. Another imperative perspective is the nonattendance of fear related to work substitution by robots. In this way, the less workers fear losing their occupations to program robots, the more it emphatically impacts the seen convenience of RPA innovation. Representatives' commonplace with RPA innovation, knowing its capabilities, don't fear substitution but or maybe see it as bolster in assignment execution. This is an important issue, as research (Lacity & Willcocks 2015; Asatiani & Penttinen, 2016; Fernandez & Aman, 2018; Hallikainen et al., 2018) shows that employees generally fear job loss to robots in cases where RPA technology is introduced.

People-related factors significantly influence both the perceived usefulness and perceived ease of use of RPA technology by employees. Social influence proved to be a significant factor, specifically how the concept of software robots is perceived by supervisors. The change involving the implementation of software robots requires management to engage in the change process and support employees. In the studied hospital, the management was the initial driving force behind the process automation, continuously supporting and personally overseeing this initiative. Trust in software robots is also a crucial area. Technology acceptance is influenced by whether it aligns with the original assumptions, whether the outcomes of the robots' work are correct, and whether the level of security is adequate, as also analysed by Lacity et al. (2015) in their studies. When many exceptions arise and robot performance needs frequent checks, the work process becomes longer, and employees become uncertain about the correctness of the tasks for which they are responsible. Similar observations are made by Willcocks (2020) in his discussions on automation and the future of work. It seems natural that the ability to assist with IT operation issues impacts the level of acceptance of RPA technology. An employee who feels confident using a particular IT solution recognizes the potential of that tool. Employees with higher competencies in using technological solutions will handle RPA technology better. Direct user engagement in the functioning of RPA, expressed through knowledge of its assumptions and capabilities, positively influences the perceived usefulness of RPA technology and its ease of use.

The seen ease of utilize of RPA innovation too depends on structure-related variables, counting the concentrated of coordinate supervision by somebody commonplace with the operation of program robots and the capacity to contact an individual who can help with robot-related issues. The compatibility of computer program robots with the work fashion moreover plays a noteworthy part, guaranteeing improved and more focused on fit. This is often affirmed by thinks about conducted in particular businesses, such as HR (Balasundaram & Venkatagiri, 2020), managing an account (Romao et al., 2019), and inspecting (Huang & Vasarhelyi, 2019).

An appropriate organizational structure, direct contact with supervisory personnel, and a good fit within organizational units where robots are used condition the perception of RPA technology as easy to use. It is additionally basic to prepare the organization with assets vital for the viable and proficient operation of program robots, such as fitting gear, reasonable workstations, and steady associations. These assets permit representatives to centre on the substantive perspective of working with program robots, subsequently reinforcing organizational flexibility, as watched in thinks about conducted in Clean organizations executing RPA (Sobczak, 2022). It is additionally pivotal to consider joining a steady organizational unit, such as a staff or outside unit, to encourage collaboration with program robots or adjust the operational demonstrate, for occurrence, by organizing Centres of Greatness (CoE), as recommended within the investigate by Anagnoste (2018), Kedziora & Penttinen (2021), and Marciniak & Stanisławski (2021a, 2021b).

Conclusion

RPA can be applied to various business processes across multiple departments. However, the implementation of RPA within an organization varies depending on its structure, business process flow, and decision-making process.

In the task domain, it was observed that employees who better understand and can explain the outcomes of software robots perceive the technology as more useful. A key factor is also reducing employees' fear of being replaced by robots, which significantly influences the positive perception of RPA as support rather than a threat to the work of hospital staff. Implementing RPA in a hospital also requires well-planned technological infrastructure and technical support to ensure the continuity of system operations. An important element is establishing appropriate mechanisms for monitoring and managing software robots, which will ensure process efficiency and minimize the risk of errors.

People-related factors, such as social influence and managerial involvement in the implementation process, are also critical for technology acceptance. Employees with greater trust in robots, confidence in the accuracy of results, and a sense of security in working with RPA are more likely to embrace the new technology. It is also important for employees to have the necessary technological skills that facilitate the use of the RPA system.

In the organizational structure domain, the availability of direct technical support and the alignment of RPA technology with the hospital's specific work environment proved to be significant factors. Proper organization, technical resources, and structural support, such as establishing Centres of Excellence, are essential for the acceptance of RPA technology, defined as perceived ease of use.

The implementation of RPA technology is undoubtedly a change, where it is crucial to understand that it does not replace medical staff but supports them in performing daily tasks, such as patient registration, service billing, processing test results, or managing medical documentation. This allows employees to dedicate time to patients and focus on more creative tasks that require specialized knowledge.

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WSB University
DąbrowaGórnicza,Cieplaka1c,tel.:+48322959359,e-mail:wydawnictwo@wsb.edu.pl