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Index of Digital Transformation: measuring the digital maturity of companies listed on the Warsaw Stock Exchange

Dominika Bosek-Rak,[a] Daniel Kaszyński[b]

Abstract. The ability to perform an efficient digital transformation is one of the key capabilities which assures company competitiveness in turbulent times. The ongoing discussion on how to measure digital maturity was the inspiration behind the main aim of the research described in the article, i.e. to construct a digital maturity model called the Index of Digital Transformation (IDT). It is built on four pillars: Strategy, Financing, Technology and Organisation. The final assessment of the model is based on a survey of 205 executives, representing companies listed on the Warsaw Stock Exchange, who were asked to provide information on their companies' performance before, during and after the COVID-19 pandemic. Statistical methods were used to calculate and validate the IDT. A significant increase in digital maturity over this period was reported in all four pillars. Moreover, the research showed that both the type of the industry and the size of the company matter. B2C industries seem to have been under greater digitalisation pressure in the pandemic period. Larger companies (which belong to WIG20, WIG40 and WIG80) were more digitally mature than the rest, and those belonging to WIG40 demonstrated the highest increase in digital maturity in the analysed period. The IDT allows a better understanding of the dynamics of digital transformation in turbulent times and provides a framework for the measurement of digital maturity.

Keywords: digitalisation, digital transformation, Warsaw Stock Exchange, digital maturity model, Index of Digital Transformation (IDT)

JEL: O33, M15

1. Introduction

Digital transformation (defined by Reddy and Reinartz (2017) as 'the use of computer and internet technology for a more efficient and effective economic value creation process') is one of the megatrends that shape the business today and impact all aspects of management. The implementation of sophisticated technologies provides a competitive advantage and is often essential to survive in a dynamic, constantly changing business environment. This phenomenon has been well-understood since the 1990s; however, the rise of mobile technology which started around 2010 has offered unprecedented technological opportunities (Schallmo & Williams, 2018). Since then, cloud computing, machine learning and blockchain have been widely

[a] SGH Warsaw School of Economics, Department of Management Theory, ul. Madalińskiego 6/8, 02–513 Warszawa, Poland, e-mail: dbosek@sgh.waw.pl, ORCID: https://orcid.org/0000-0002-0831-0439.

[b] SGH Warsaw School of Economics, Institute of Econometrics, ul. Madalińskiego 6/8, 02–513 Warszawa, Poland, ORCID: https://orcid.org/0000-0002-0865-0732.

implemented. At present, Artificial Intelligence (AI) is the technology expected to have a profound impact on the global economy. Bughin et al. (2018) estimated that the use of AI should boost global GDP by 1.2% annually by 2030. The International Monetary Fund (2024) predicts that 40% of jobs will be affected by GenAI. Other technologies like cloud computing, the Internet of Things, machine learning, blockchain and mobile phones also have an influence on how businesses are run.

Looking at international comparisons, Poland ranks very low compared to other European Union countries in terms of digitalisation. According to the Digital Economy and Society Index (2024) published annually by the European Commission, in 2023, only Bulgaria, Romania, and Greece ranked lower than Poland. The Digital Enterprise pillar, which measures the percentage of companies with successful technology implementation, seems to be Poland's especially weak point.

The objective of this study is to propose a framework for understanding the digital maturity of companies listed on the Warsaw Stock Exchange (WSE), to show the change of this maturity over time and to identify its basic differentiators. Therefore, the following research questions have been formulated:

- How to measure companies' digital maturity in a comprehensive way?
- What was the level of digital maturity of the companies listed on the WSE before, during and after the COVID-19 pandemic?
- Which industries experienced the greatest increase in digital maturity between 2018 and 2023?
- Did larger companies tend to be more digitally mature than their smaller counterparts?

The article thus aims to contribute to the discussion on measuring digital maturity. The results of the analysis are also expected to provide empirical evidence on the digital transformation 'journey' of companies listed on the WSE during the time around the COVID-19 pandemic. As per a recent overview by Thordsen and Bick (2023), the literature on the subject describes numerous attempts that have been made to measure digital maturity and the many controversies that emerged around this topic. Therefore, we decided to develop our own approach to assess companies' digital maturity based on numerous questions asked in an executive survey conducted among board members and digital transformation leaders of listed companies. This approach made it possible to collect the details on digital transformation directly from companies, as typically such information is not publicly available.

The paper is structured in the following way: Section 2 presents the theoretical considerations and a literature review and proposes an original digital maturity model. Section 3 shows the results of the empirical study conducted among 205 companies listed on the WSE, focusing on their digital maturity and its differentiators. The Conclusions part describes the implications, limitations and a further research agenda.

2. Theoretical background and literature review

2.1. Digital maturity and competitive advantage

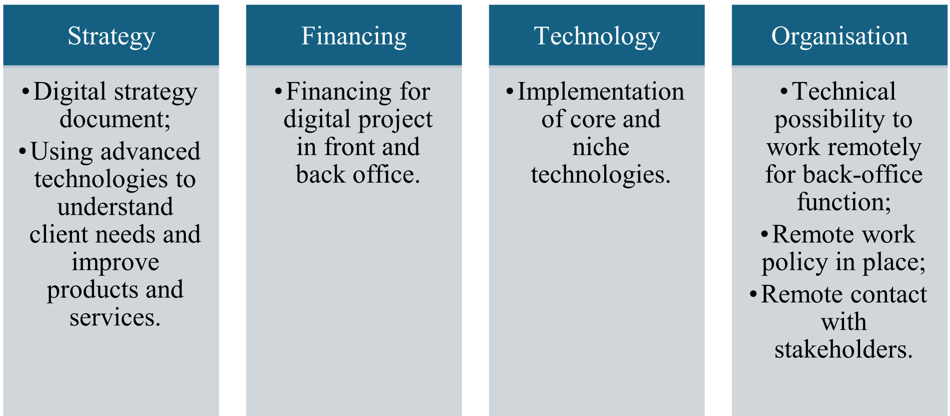
One of the key objectives of every company is to generate profit, which can be done through the continuous building of sustainable competitive advantage on the market (Porter, 1985). Strategic management theories provide explanations and guidance on how it can be done efficiently, either by means of market positioning (Porter, 1985) or through the company's own resources (Barney, 1991). There are also approaches that combine the two, which seems to be optimal in times of high uncertainty and rapid change. Under the dynamic capabilities approach (Teece et al., 1997), the most successful companies are able to combine timely responsiveness, a rapid and flexible product and services innovation, together with the management-related ability to effectively coordinate and deploy internal competences and external opportunities. 'Dynamic' relates to the ability to renew competences, especially technological ones, to meet the requirements of the constantly changing environment, while 'capabilities' refer to managerial skills to adapt, integrate and reconfigure organisational skills and resources. Therefore, implementing new technologies and running digital transformation programmes is perceived as a path to remaining competitive in a rapidly changing business environment (Ferreira et al., 2019; Warner & Wäger, 2019) and improving business performance (Eremina et al., 2019). Thus, digital maturity seems to be a good indicator of the market position of a company, its competitive advantage and its potential for future success. Especially during the COVID-19 pandemic crises, digital maturity was perceived as a basis to staying resilient (Viana et al., 2023), and the maturity of digital strategy in particular assured this resilience (Forliano et al., 2023). For example, in 2020, the most digitalised companies in each industry noted a smaller decrease in productivity (by 20%) than that of entities digitalised to a lesser extent (IMF, 2024). Moreover, the COVID-19 pandemic boosted digital transformation, as managers (even the most reluctant ones) were forced to accelerate the implementation of remote work and paperless operations (Amankwah-Amoah et al., 2021). Thus, we may assume that companies in Poland also achieved a significant increase in digital maturity during this period.

2.2. Measuring digital maturity

The first objective of this research is to propose a comprehensive tool to measure enterprise digital maturity. The assessment of a firm's digital maturity is perceived as a critical step in achieving a higher degree of organisational performance (Bititci et al., 2015). Digital maturity models are typically built to guide firms through digital transformation and are defined as 'normative reference frameworks that organizations apply to determine their present state of digital maturity and thus of their digital transformation across its various building blocks and levels' (Williams et al., 2019). According to Ochoa-Urrego and Peña's (2020) systematic literature analysis, the average digital maturity model comprises of the following dimensions: Technology, Digital Culture, Operational Processes and Digital Strategy. The aim of these models is to identify companies which are digitally mature, i.e. in 'A state of constant anticipation and adaptation to an ever-changing environment. Particularly the ability to critically reflect on and monitor business performance, together with a willingness to evolve permanently' (Thordsen & Bick, 2023). The key controversies around digital maturity models involve a poor theoretical base and limited empirical evidence associated with insufficient documentation on the development of the maturity models in general (de Bruin et al., 2005), as well as a lack of academic validity and rigor (Teichert, 2019).

Inspired by these theoretical considerations, our proposed digital maturity model is based on four pillars: Strategy, Financing, Technology and Organisation. These pillars derive from the capacities of dynamic capabilities, introduced by Teece (2014): sensing, seizing and transforming. Strategy is an essential dynamic capability in the context of digital maturity. It makes it possible to sense which digital technologies are able to best address client needs and develop more suitable products and services, as well as preparing a relevant formal digital strategy document (Yeow et al., 2018). Financing is the pillar that embodies the seizing capability. In order to implement a strategy, the company must mobilise its resources, including the financial ones. Investing in digital projects enables the organisation to seize the opportunities that were identified in the sensing phase. The last two pillars (Technology and Organisation) can be classified as a transforming capacity. Digitally mature companies which aim at staying competitive strive for a constant reconfiguration of their resources through the implementation of the most recent technologies, both core and niche ones, across functions. As improving the digital maturity of the workforce is considered the key dynamic capability (Warner & Wäger, 2019), remote work possibilities and remote communication with the stakeholders are viewed as proxies to assess the ability of the organisation to adapt quickly to the new digital reality.

Figure 1. Digital maturity model



Source: authors' work.

Being inspired by the digital maturity models described in the literature (Thordsen & Bick, 2023) and rooted in the dynamic capabilities approach, this model allows a precise measurement of companies' digital maturity, as the components of the pillars are well-defined (see Figure 1).

2.3. Company size and industry as determinants of digital maturity

All companies operate in a unique environment and have a unique set of resources at their disposal, so their digital 'journey' must be adjusted to these conditions. Considering the dynamic capabilities approach, an industry can be perceived as an external, but specific for all players, market condition (Strønen et al., 2017), under which all industry players compete. The size of the company can be viewed as one of the factors which determines its internal ability to react to change (Jeng & Pak, 2016). Thus, theoretically, these two variables could differentiate companies' digital maturity.

Horváth and Szabó (2019) noticed that smaller companies typically focus on a single niche market and are less flexible, whereas big ones experience higher pressure from their competitors and shareholders. Their management teams carefully monitor the opportunities that digital technologies create. They have enough capabilities to react relatively quickly. Digital transformation needs sufficient funding, as sustainable successful digital initiatives require scale (Kane et al., 2017). Therefore, the larger the size of the company, the higher the level of digital maturity. On the other hand, excessive resources can cause larger companies to focus less on efficiency. Although smaller companies' responsiveness is hindered by restrained financial capability (Mittal et al., 2018), some believe that it is these restraints that might force a company to be more innovative (Katila & Shane, 2005). Due to the variety of research results, it is worth analysing if there are significant differences in digital maturity of big and small companies listed on the WSE.

The assumption that the industry matters while assessing digital maturity is based on the belief that companies can be clustered into industries which constitute a relatively similar and specific competitive environment for them. Therefore, all companies which belong to a given industry operate under similar conditions and circumstances in terms of digitalisation, and face similar barriers (Senna et al., 2023). Since all participants operating in an industry face the same disruptive change which is an external driver of digital transformation (Verhoef et al., 2021), intense competition within the industry helps them to stay competitive, especially if they are efficient in their digital transformation efforts (Bergek et al., 2013). During the COVID-19 pandemic, all companies were forced to digitalise; however, industries where face-to-face contact is essential were forced to accelerate their digital transformation leading to a significant increase in digital maturity (Fletcher & Griffiths, 2020). Therefore, it is reasonable to check whether there are any significant differences between industries in terms of their level of digital maturity, and which industries experienced the largest increase in digital maturity.

2.4. Digital maturity of companies in Poland

As digital transformation is essential to Polish listed companies (Klimczak et al., 2022), there are several publications on digital transformation and digital maturity. The digital maturity of Polish companies is carefully observed mainly by consulting companies which publish their assessments on a regular basis (e.g. KPMG Business Digital Transformation Monitor, EY Digital Transformation). They often focus on all types of companies, though, including private ones. Kowal et al. (2024) analysed the level of digitalisation of Polish companies in the context of the COVID-19 pandemic; however, they based their assessment on secondary research, i.e. three existing industry reports. Chądrzyński et al. (2021) also described the digitalisation of Polish enterprises on an aggregate level based on widely-available information on Internet access, websites and specialists.

The size and industry determinants of digital transformation in Poland were only partially evaluated in the literature. The main focus there is on small and medium-sized enterprises (SMEs) (Mieszajkina & Myśliwiecka, 2022) and microenterprises (Pawełoszek et al., 2023), and emphasize the lack of scale and high costs as key barriers to digitalisation. Although some industries have been assessed, e.g. development services (Winnicka-Wejs, 2022) or the industrial sector (Grzyb, 2019), there is no comprehensive industry comparative study available.

In short, very limited academic research on this topic preceded our primary research conducted among companies listed on the WSE; the research results in this area allow a better understanding of the dynamics of their digital transformation and digital maturity.

3. Empirical specification and data

3.1. Sample and data

The analysis is based on an executive survey of 205 companies listed on the WSE. The survey was conducted in the form of a questionnaire. The questions were related to the implemented technologies, the assumed priorities in the digital transformation, the use of technologies to understand clients' needs and enhance products and services, the digital strategy, the budget for digital initiatives and remote work, and communication with stakeholders. Answers provided by the companies regarded three observation periods: before (2018–2019), during (2020–2021) and after (2022–2023) the COVID-19 pandemic. The final IDT is calculated at company level and can be further aggregated into industry level.

The survey respondents were mostly top executives who declared themselves to be well-informed and participating in the company's digital transformation. The survey was conducted through a Computer-Assisted Web Interview (CAWI). Despite the respondents' potential subjectivity, we believe that due to the high number of respondents and the extensive coverage of the total population (~25%), the factual description of the digital maturity of the companies listed on WSE could be identified.

3.2. Methodology

The IDT is a metric calculated as a simple average of the obtained results relating to the four pillars described in the previous section: Strategy, Financing, Technology and Organisation. Its formula is as follows:

$$DI_i = \frac{\mathrm{STR}_i + \mathrm{FIN}_i + \mathrm{TECH}_i + \mathrm{ORG}_i}{4}, \tag{1}$$

where:

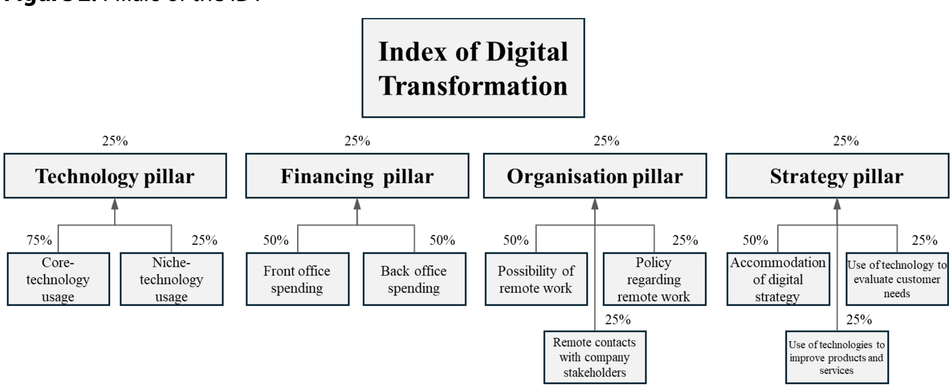
DI_i is the value of the IDT for the i-th company,
STR_i is the digital strategy of the i-th company,
FIN_i is the spending on digitalisation,
TECH_i is the technology used in the i-th company,
ORG_i is the organisational part of the digitalisation of the i-th company.

The simple average was chosen to reflect the equal importance of each pillar. The resultant value representing the advancement of each of the pillars (weighted average of the particular pillars) is based on the answers provided to the composed set of questions allowing the evaluation of the pillar-based maturity. Below, we present a scope of questions that were used within a particular pillar. Each pillar consists of two or three categories which are weighted according to their importance to create a comprehensive and substantial picture of the digital maturity of each company:

- Technology comprises two sets of questions (weights in the brackets): core-technology usage (75%) and niche-technology usage (25%);
- Financing consists of questions related to spending on digitalising the front office (50%) and the back office (50%);
- Organisation covers a broader set of questions that are linked to the possibility of remote work (50%), remote work policy (25%) and remote contacts with company stakeholders (25%);
- Strategy refers to questions concerning the accommodation of digital strategy (50%), the use of technology to evaluate the needs of the customers (25%), and the use of technology to improve products and services (25%).

The range of the answers to each question was set to 0 and 1, where 0 referred to the lowest advancement in the particular field and 1 to the highest. For each company, the value of every pillar was calculated as the weighted average of the answers. The high-level calculation methodology is presented in Figure 2.

Figure 2. Pillars of the IDT



Source: authors' work.

As digital transformation is very dynamic, the scale has not been proposed; due to dynamic changes in the technological landscape of the available solutions/tools, we recommend comparing the dynamics of the digital maturity index rather than evaluating particular companies' digital maturity level alone.

Each of the pillars combines several questions (binary or the Likert scale), i.e.:

- Technology – 13 questions;
- Financing – 2 questions;
- Organisation – 13 questions;
- Strategy – 27 questions.

The basic descriptive statistics of the research sample (companies) has been presented in Table 1.

Table 1. Descriptive statistics of the research sample

Pillar		2018–2019	2020–2021	2022–2023
	number	205	205	205
Technology	min	0.00	0.00	0.00
	max	0.87	0.89	0.97
	mean	0.19	0.31	0.44
Financing	min	0.00	0.00	0.00
	max	1.00	1.00	1.00
	mean	0.18	0.37	0.52
Organisation	min	0.08	0.23	0.25
	max	0.96	1.00	1.00
	mean	0.50	0.61	0.69
Strategy	min	0.00	0.02	0.19
	max	1.00	1.00	1.00
	mean	0.65	0.76	0.84
Digital Index	min	0.08	0.15	0.20
	max	0.88	0.97	0.99
	mean	0.38	0.51	0.62

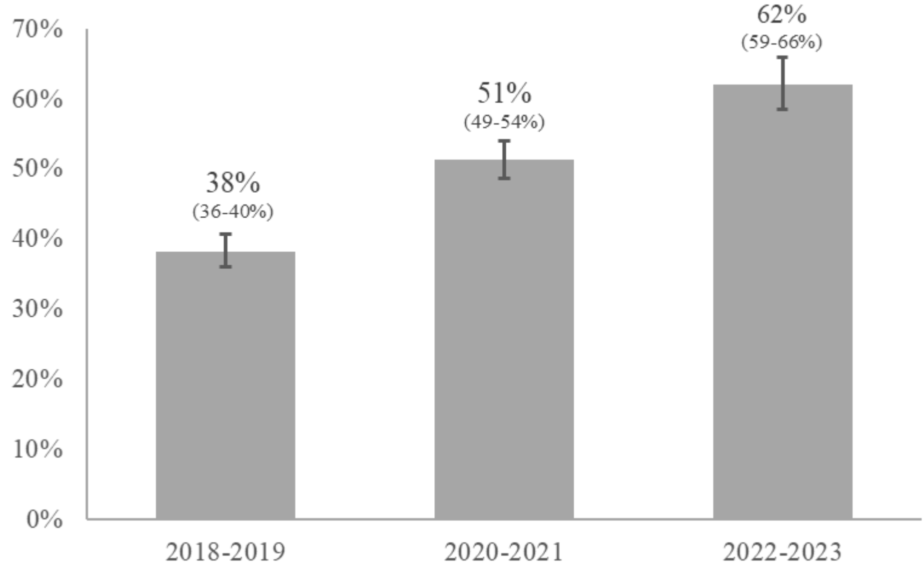
Source: authors' work.

3.3. Results

The IDT described above has been calculated for each of the 205 surveyed companies listed on the WSE. All of the calculations were performed on cloud (GCP) using Python 3.6 (in particular the *numpy*, *pandas* and *scipy* libraries).

The average IDT was growing over the analysed periods. The average values of the IDT are presented in Figure 3.

Figure 3. IDT: yearly aggregates

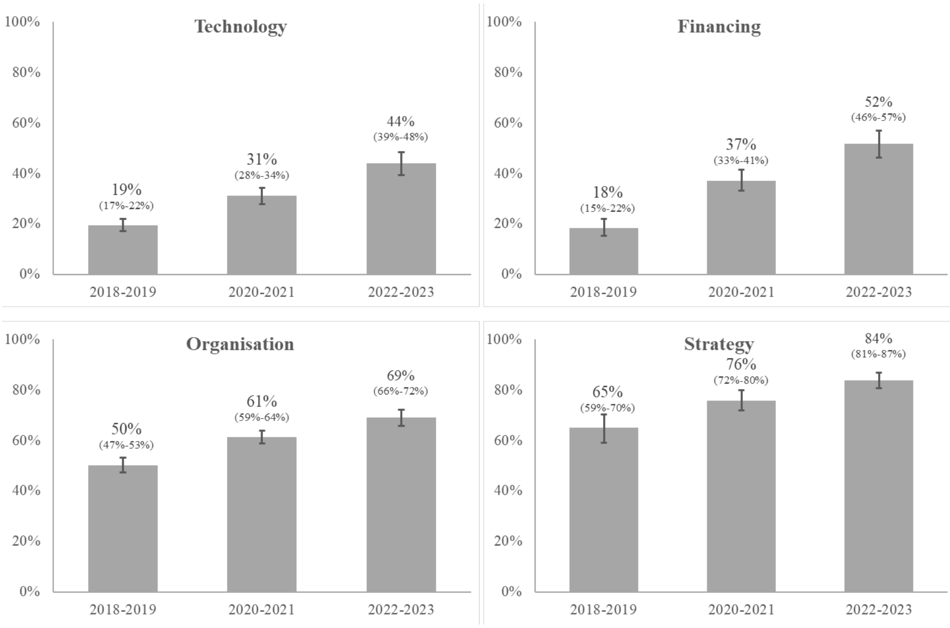


Source: authors' work.

Note that the grey bar presents the average within a particular observation period, while the black whiskers represent a 99% confidence interval of the IDT (calculated using bootstrapping; see Efron (1992)). Due to the IDT being non-normally distributed in every period (H0 rejection at 1% statistical significance of the Shapiro-Wilk test), the differences in the IDT were tested using the Friedman test for all of the periods, i.e. in 2018–2019, 2020–2021 and 2022–2023; the periods consist of statistically different distributions of the IDT (Friedman test statistic = 314.52, H0 rejected at 0.1%).

In terms of the pillars, Figure 4 presents the time dynamic of the average aggregates; the Financing pillar was the one with the most dynamically increasing value over the 2018–2023 period. Companies, on average, scored almost 3 times more in the Financing pillar after the COVID-19 pandemic than in the pre-pandemic period. The pandemic was the time when implementing technology was necessary to stay competitive and to survive on the market, hence the significant increase in the Technology pillar; moreover, these implementations required funding which was relatively easy to obtain due to low interest rates and government support programmes (Dębkowska et al., 2021). Strategy was the least dynamically increasing pillar, which may have been related to the high base in the period before the COVID-19 pandemic.

Figure 4. IDT pillars: yearly aggregates



Source: authors' work.

Note that the grey bar presents the average value of a pillar within a particular observation period; the black whiskers represent a 99% confidence interval of the IDT (calculated using bootstrapping).

As an additional layer of the analysis, the correlation between the pillars forming the IDT for the sample under study has been calculated and presented in Table 2.

Table 2. Pearson correlation coefficient between the pillars forming the IDT

2018–2019	Technology	Financing	Organisation	Strategy
Technology	1.00			
Financing	0.44	1.00		
Organisation	0.34	0.21	1.00	
Strategy	0.10	0.18	0.24	1.00

2020–2021	Technology	Financing	Organisation	Strategy
Technology	1.00			
Financing	0.64	1.00		
Organisation	0.57	0.37	1.00	
Strategy	0.49	0.41	0.37	1.00

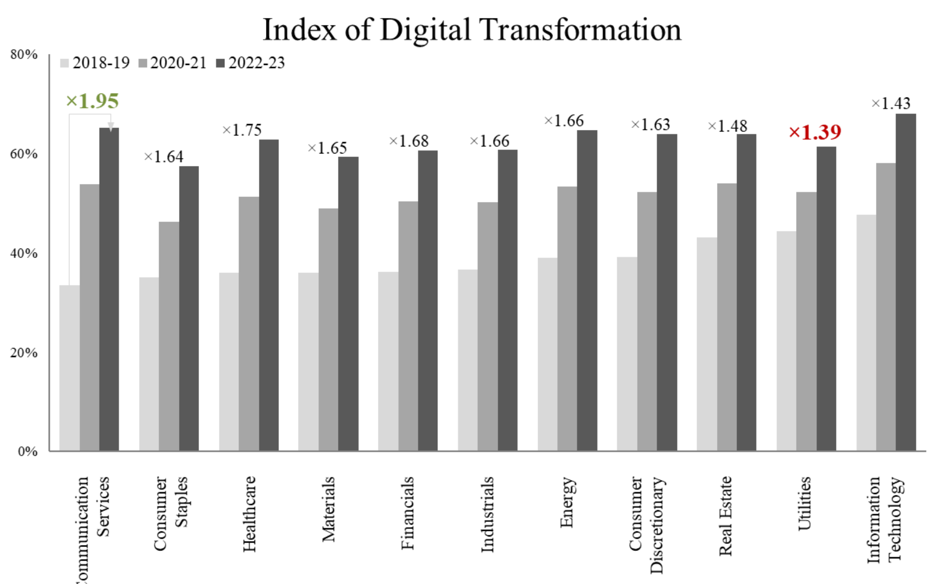
2022–2023	Technology	Financing	Organisation	Strategy
Technology	1.00			
Financing	0.78	1.00		
Organisation	0.73	0.67	1.00	
Strategy	0.70	0.56	0.59	1.00

Source: authors' work.

The upward trend is visible both at the aggregate level and across all the examined sectors of the economy. An interesting phenomenon is the implied sequence of changes occurring within companies (based on the presented aggregates), which is in line with the typical strategic management process focusing firstly on creating a strategy and then implementing it through proper resource allocation (Sinnaiah et al., 2023). In this case, a digital strategy is developed first and action is taken to establish digital channels of communication with the stakeholders (customers, employees, suppliers), and only then do financial expenditures on digitalisation projects increase and the implementation of advanced modern technologies occurs. Introducing and developing digital channels seems easy to accomplish. Thus, it can be defined as a digitalisation phase, as compared to the implementation of advanced technologies, e.g. artificial intelligence, which is a rather more expensive and sophisticated digital transformation phase (Verhoef et al., 2021). This indicates that companies are likely to make decisions regarding digital transformation projects thoughtfully, analysing their potential costs and benefits before proceeding to their implementation.

However, the situation varies between industries. The most advanced in terms of the level of digital maturity are the IT (with an average value of the index of 68% in 2022–2023) and Communication Services sectors (65%) (see Table 3). The least advanced, on the other hand, are Consumer Staples (mainly the food industry) (57%) and Materials (59%).

Figure 5. IDT: yearly aggregates within sectors



Source: authors' work.

Table 3. IDT: results per industry

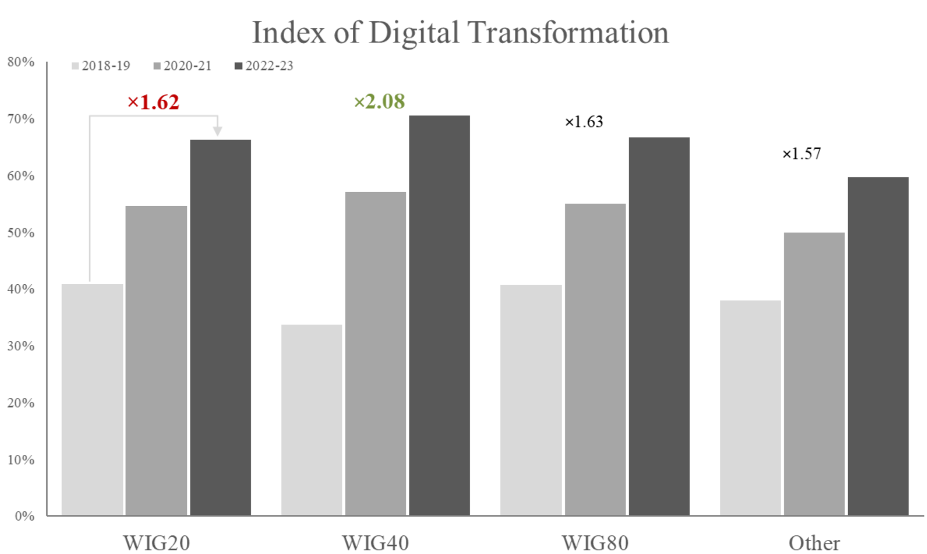
	Communication Services	Consumer Discretionary	Consumer Staples	Energy	Financials	Healthcare	Industrials	Information Technology	Materials	Real Estate	Utilities
2018–2019	0.33	0.39	0.35	0.39	0.36	0.36	0.37	0.48	0.36	0.43	0.44
2020–2021	0.54	0.52	0.46	0.53	0.50	0.51	0.50	0.58	0.49	0.54	0.52
2022–2023	0.65	0.64	0.57	0.65	0.61	0.63	0.61	0.68	0.59	0.64	0.61

Source: authors' work.

The top three industries with the most dynamic increase were (see Figure 5): Communication Services, Healthcare and Financials. These are industries with a high exposure to retail customers (B2C) and during the pandemic, they were under greater pressure to digitalise.

As the sample was representative in terms of the size and industry (see the Table in the Appendix), an analysis was conducted based on the stock exchange index which the company belongs to. Interestingly, medium-sized companies (WIG40) at that time reached the index's highest level (see Figure 6.). The largest companies (WIG20), despite having an initially high level of digital maturity, showed a low growth rate in this area. In contrast, the smallest companies (other) at that time had the lowest level of digital maturity and a low growth rate of this indicator over time. This shows that medium-sized companies are large enough to leverage advanced technological solutions without encountering competency barriers and small enough to avoid organisational challenges during their implementation (see Figure 6.).

Figure 6. IDT: yearly aggregates within stock exchange indices



Source: authors' work.

4. Results and interpretation

The digital maturity model, which consists of four pillars: Strategy, Financing, Technology and Organisation, was designed on the basis of the dynamic capabilities approach, allowing the measurement and assessment of the digital maturity of the companies listed on the WSE. As expected, these companies accelerated their digitalisation during the COVID-19 pandemic. The increase in digital maturity between the pre-pandemic and post-pandemic era amounted to 24 p.p., i.e. from 38% to 62%.

Our results show that digital maturity, on average, increased across the studied companies during this period, which is in line with the findings of Kowal et al. (2024) and Chądrzyński et al. (2021) regarding Polish companies during the pandemic. Moreover, the size of the company matters when it comes to digital maturity. Companies which belong to WIG40 are the most digitalised, which is only partially consistent with the expectations. What is surprising is that the largest companies which have greater economies of scale are not the most digitalised, as Horváth and Szabó (2019) suggested. This can be explained by their excessive bureaucracy and the resulting operational challenges (Meyer et al., 2011). Medium-sized companies seem to be large enough to have economies of scale and at the same time they are small enough to have operational agility (Radicic & Petković, 2023). The low digital maturity observed among the smallest companies was expected and consistent with the previous research (Mieszajkina & Myśliwiecka, 2022).

Digital maturity and its dynamics vary across different sectors of the economy (Bergek et al., 2013; Verhoef et al., 2021). Industries with a high exposure to consumers were under greater pressure to digitalise during the pandemic (Fletcher & Griffiths, 2020). This is also visible in our results, as industries with a focus on services for retail consumers have reported higher acceleration and a higher absolute level of digital maturity. On the other hand, industries focusing on business clients and manufacturing remained on a relatively lower level of digital maturity.

5. Conclusions

Being a key dynamic capability in the era of digital transformation, the ability to implement new technologies and be digitally mature is crucial for every company to remain competitive.

As companies operate in a very dynamic environment and face constant technological change, they struggle to benchmark themselves against their competition. The proposed Index of Digital Transformation is expected to be a useful framework to measure digital maturity and understand market position for every company in every industry.

The presented framework can be considered as an important contribution to the ongoing discussion on how to measure digital maturity in an efficient way. It can be used and further developed by scientists as the rapid technological change continues. Since our digital maturity model is deeply rooted in the theoretical frameworks of strategic management, it is universal and can be used even if technological trends evolve quickly and unexpectedly.

The example of companies listed on the WSE showed that digital transformation accelerated during the COVID-19 pandemic. This is again an indirect proof that this extraordinary situation brought significant breakthrough for the society, economy and business.

Then, both the size of the company and the industry in which it operates proved significant differentiators, so these two factors should be considered by business entities while planning potential future initiatives aiming to enhance digital maturity and by all other market participants (e.g. policy makers, investors) to better understand the dynamics of digital transformation.

However, our research on the digital maturity of Polish companies faced some limitations.

The focus was on Poland and only on listed companies, so the results cannot be easily generalised. The research is based on executive surveys which may not be fully objective and may not show all aspects of the digitalisation of a company.

Another potential bias in this study is the fact that the survey respondents answered the questions regarding three different points in time at once. This could lead to the 'present conditions perspective' and make the trend more upward, as all companies made some progress in digitalisation over the pandemic period due to rapid technological change and specific market conditions.

Further research into digital maturity should focus not only on the size of companies and industry they operate in, but also on organisational culture which is an important differentiator as well (Horváth & Szabó, 2019). Since the analysis concerns only companies listed on the WSE and was inspired by the research done by Meyer et al. (2011), it would be interesting to find out how the digital transformation process went in the subsidiaries of transnational corporations which operate in Poland, as well as in small and medium-sized enterprises, and what degree of digital maturity they achieved. To make the study more comprehensive, the next iteration of the IDT might involve the categorisation of the companies into clusters, as proposed e.g. by Estensoro et al. (2022). Additionally, a deeper analysis of the sequence of the digital maturity improvement and the motivations behind the decision would be valuable and worth investigating in future research studies.

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Appendix

Table. Structure of the sample

Industry	WIG20	WIG40	WIG80	Other	Total
Communication Services				10	10
Consumer Discretionary	2	2	4	16	24
Consumer Staples		1	1	11	13
Energy	1	1	1	1	4
Financials	2	1	3	10	16
Healthcare		2	4	9	15
Industrials		2	12	40	54
Information Technology		2	4	15	21
Materials	3	1	7	18	28
Real Estate		1	3	9	13
Utilities	2	1	1	2	6
Total	10	14	40	141	205

Source: authors' work.

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The share of expenditure on food and energy in total spending of Polish households in 2021 taking into account energy poverty

Kornelia Kłopecka[a]

Abstract. The article concerns the share of expenditure on food and energy in the total spending of Polish households in 2021. The main objective of the study is to find out which socio-economic characteristics of Polish households determine how big the share of expenditure on food and energy in households' total spending is, as well as to examine how energy poverty affects this expenditure. Tobit models estimated using the maximum likelihood method were used in the empirical study. The estimation results indicate that the household size and type, disposable income, extent of energy poverty, and being a retiree, a pensioner or a farmer is correlated with how big the share of expenditure on food and energy in a household's total expenditure is.

Keywords: energy poverty, household budgets, Tobit model, share of expenditure on food and energy
JEL: D12, D13, Q41

1. Introduction

The study of the socio-economic determinants of the share of food and energy expenditure in household budgets in Poland is a significant contribution to the literature on quality of life, consumption levels and energy poverty. Expenditure on food and energy reflects basic human needs, and its level directly impacts the physical and mental wellbeing of society. Previous research showed that the share of expenditure on food and energy is dependent on various factors, including the household size, disposable income, location (class), household composition and even belonging to specific social groups.

In the literature on energy poverty, studies analysing the impact of energy costs on quality of life and limitations on access to essential energy services are of particular importance (Bouzarovski, 2014). Researchers also identify energy-poor households facing the 'heat or eat' dilemma. This term, frequently used in research, refers to a situation where a family, due to limited financial resources, is forced to make difficult choices between heating their home and buying food. In the United

[a] Krakow University of Economics, College of Economics, Finance and Law, Institute of Quantitative Methods in Social Sciences, ul. Rakowicka 27, 31–510 Kraków, Poland, e-mail: k.klopecka@gmail.com, ORCID: https://orcid.org/0009-0006-8484-2847.

Kingdom for example, certain organizations provide free heating services to those in need, including older people and people with disabilities (Champagne et al., 2023).

The innovativeness of this study lies in the fact that it combines the analysis of the share of food and energy expenditure in the total spending of households with that of energy poverty. This allows a better understanding which households are most vulnerable to energy poverty and how the share of their food and energy expenditure in their total spending is shaped. Understanding how energy poverty affects the share of this expenditure can provide valuable insights for policy-makers in formulating strategies to combat energy poverty.

This topic was chosen for our research partly due to the aggravating issue of energy poverty in the face of global crises, such as the COVID-19 pandemic and rising energy commodity prices. The inability to satisfy basic needs, such as food, heating and electricity, directly affects the wellbeing of society. High food prices might lead to malnutrition, while rising energy costs might limit a household's access to heating and electricity, impacting the health and quality of life of its members. Previous research focused predominantly on analysing expenditure on food and energy, but few studies so far have examined the impact of energy poverty on the structure of this expenditure.

The aim of this study is to determine which socio-economic characteristics of Polish households have a significant influence on how big the share of food and energy spending in their total expenditure is. As mentioned before, this research brings a new perspective to the existing literature by combining the analysis of expenditure on food and energy with the problem of energy poverty. To achieve this goal, Tobit models estimated by means of the maximum likelihood method were applied.

The results of the study provide valuable insights that can help to develop solutions to counteract energy poverty and shape effective state policy in this respect. Our research also contributes to the better understanding of the relationships between energy poverty and socio-economic factors, which is crucial for creating policies aimed at sustainable development and improving the wellbeing of societies.

2. Literature review

When analysing choices of food and decisions regarding consumption, it is essential to consider the demographic factors (household size) as well as the psychological (lifestyle), economic (disposable income), social, cultural and globalisation-related ones (Kostakis, 2014). Research findings (Hanus, 2018) have shown that the latter, i.e. the impact of globalisation on consumers' eating habits, is reflected in behaviors such as purchasing food products in supermarkets and seeking convenience and ease in food consumption. New consumer preference trends, partly driven by the globalisation, have forced producers to develop innovative and personalised products to meet diverse consumer needs.

Analysing external factors, certain correlations between food expenditure and household income can be observed (Zani et al., 2019). According to Engel's law, as income increases, the percentage of food expenditure in a household's total spending decreases (Sekhampu, 2012). It is also shown that the higher the level of education of household members, the more balanced diet in this household is. Such families tend to spend relatively much on varied types of food products (Maniriho et al., 2021). Another important factor is the household's size – as the number of members increases, so does the percentage of income spent on food (García & Grande, 2010).

In the literature, household consumption expenditure is also analysed according to the classification of location (Borowska et al., 2020; Grzega, 2015, 2022). The presented results indicate that the share of food expenditure in the overall expenditure structure is larger among households in rural areas than those in cities. As regards expenditure on housing and energy, on the other hand, rural households overall spend less than households in cities.

The household composition is also mentioned in the literature as a determinant of the share of food expenditure in the total spending of a household (Grzega, 2015). Such studies show that couples without children devote a smaller share of their budgets to food than both couples with children and single parents with dependents.

Other studies highlight the significance of the socio-economic status of a household in the context of expenditure on food and energy (Utzig, 2016). The research shows that households of people in employment devote a smaller share of their budgets to food than households of farmers and pensioners. However, households of pensioners spend proportionally more on housing and energy than people in employment and farmers.

Apart from the above-mentioned factors, certain relationships between food expenditure and age can be observed. As the age of the household members increases, so does the level of food expenditure (Turczak & Zwiech, 2014). However, a significant change in the overall structure of food expenditure occurred due to the introduction of the 'Family 500+' benefit. This influx of income translated into households' higher spending on food products, particularly in the case of the rural ones (Wiśniewska, 2017).

Energy poverty is also significant in the context of household expenditure, and it has gained importance in recent years in the economic and social research. Relevant literature indicates, as mentioned before, that energy-poor households often face difficult choices between paying energy bills and buying food (Bouzarowski, 2014). Research shows that energy poverty impacts the overall level of household expenditure (Thomson et al., 2017).

A study of household budgets in Poland showed that in 2022, expenditure on food and non-alcoholic beverages had the largest share in the expenditure structure of Polish households, amounting to as much as 26.7%. The level of this expenditure depends on which social group (farmers, pensioners, employed people or the self-employed) the members of a household belong to (Główny Urząd Statystyczny, 2023).

The above literature review clearly shows that important determinants affecting the share of households' spending on food and energy are: the age of household members, the size of the household, the level of education of household members, disposable income of the household, the composition of the household, the socio-economic group the household members belong to, the location of the household, and the occurrence or not of energy poverty.

3. Energy poverty

3.1. Definition

Since 2022, Poland has had a legal definition of energy poverty. It was introduced by the Announcement of the Speaker of the Sejm of 19th May 2022 on the publication of the consolidated text of the Energy Act (Journal of Laws from 21st December 2022, Item 1385):

Article 5gb. [Energy Poverty].

'1. Energy poverty means a situation where a household run by one person or by several people jointly in an independent residential unit or a single-family residential building, where no business activity is conducted, cannot ensure the sufficient level of heating, cooling or electricity for powering appliances and lighting, and where the household cumulatively meets the following conditions:
- has a relatively low income;
- its energy-related expenditure is relatively high;
- the building where the household is located is of low energy efficiency.

2. The criteria for energy poverty qualifying for energy poverty reduction programs are specified by each programme that introduces energy poverty reduction instruments'.

The above definition means that a household is considered energy-poor and qualifies for social programmes only if all the above conditions are met.

Clarifying these three measures is not an easy task, especially since data for such categories are not collected in Poland. Therefore, it is impossible to apply the definition of energy poverty to data published by state institutions. In such cases, other measures must be used. One of them is a 'subjective assessment' of a household (Śmiech et al., 2023).

3.2. Subjective assessment

To identify energy-poor households, three questions were asked to respondents during the survey:
1. In your opinion, is the house you live in sufficiently warm in winter;
2. How do you rate the timeliness of paying housing costs (rent, utility costs, including gas and electricity, etc.) by your household;
3. Which of the following statements best describes the way money is managed by your household.

The first question enabled respondents to either confirm or deny the condition. A negative response classifies the household as energy-poor. In the second question, the responses 'Rather badly/Badly' indicate energy poverty, while 'Well/Rather well/Average, neither well nor badly' indicate its absence. Two of the responses to the last question, namely 'We have to manage very frugally on a daily basis/We do not even have enough for basic needs', classify the household as energy-poor. In contrast, the remaining statements 'We can afford some luxuries/We can afford many things without special saving/We have enough for daily needs but must save for larger purchases' do not indicate energy poverty.

The results and distributions of responses to individual questions are presented in Table 1.

Table 1. Distribution of responses to the questions in our survey

Energy poverty	Absence of energy poverty
3.29%[a]	96.71%[a]
0.84%[b]	99.16%[b]
16.90%[c]	83.10%[c]

a Distribution of responses to the question: 'In your opinion, is the house you live in sufficiently warm in winter?'
b Distribution of responses to the question: 'How do you rate the timeliness of paying housing costs (rent, utility costs, including gas and electricity, etc.) by your household?'
c Distribution of responses to the question: 'Which of the following statements best describes the way money is managed in your household?'
Source: author's work based on data from the Household Budget Survey 2021.

4. Data overview and methodology

4.1. Data

The dataset used in the analysis comes from a study focusing on household budgets in 2021 conducted by Statistics Poland. This study serves as a crucial source of information on the level and structure of expenditure and income of individual households, the consumption of basic food items, housing conditions, and subjective assessment of the material condition. Furthermore, the dataset provides information on the household's classification in terms of location, belonging to a particular socio-economic group, and composition.

Numerous studies have shown that the share of expenditure on food and energy in a household's overall spending is influenced by the above-mentioned factors. Additionally, we took into account a variable describing energy poverty, which also significantly impacts the spending structure of households. The variables used in the analysis are presented in Table 2.

Table 2. Variables used in the study with descriptions

Variable	Description
X_1	Number of individuals in a household
X_2	Disposable household income
X_3	Subjective energy poverty
X_4	Location (class)
X_5	Socio-economic group
X_6	Household composition
X_7	Share of food expenditure in total expenditure
X_8	Share of energy expenditure in total expenditure
X_9	Share of expenditure on food and energy in total expenditure

Source: author's work based on data from the Household Budget Survey 2021.

Table 3 presents the basic descriptive statistics for five variables: the number of people in a household, disposable income, the share of food expenditure, the share of energy expenditure, and the share of combined food and energy expenditure in the household's total expenditure. The average number of people in a household was three. The median was two, meaning that half of the observations in the study fell below this value, and the other half were above it. The study comprised of single-person households and large families (up to 12 members) as well.

The average disposable income was 5,637.63 PLN, and the median was 4,751.85 PLN. The lowest income was negative (-48,000.00 PLN), while the highest amounted to 209,648.90 PLN. Such discrepancies in the minimum and maximum values resulted, among other things, from the specific nature of agricultural work, where farmers can earn high incomes in certain months and incur losses in other.

The average share of food expenditure in a household's total expenditure was 28%, which turned out to be very close to the value reported by Statistics Poland for 2022 (26.7%). This may be due to relatively stable consumption trends in households. The minimum values were 0, and the maximum 1. This distribution justifies the use of the Tobit model later on, because it accounts for limitations in dependent variables, whose specificity could distort classical regression models.

Table 3. Descriptive statistics of five quantitative variables

Variable	Minimum	First quartile	Median	Average	Third quartile	Maximum
Household size	1.00	2.00	2.00	3.00	3.00	12.00
Disposable income	–48000.00	2850.00	4751.85	5637.63	7200.00	209648.90
Share of food expenditure in total expenditure	0.00	0.19	0.27	0.28	0.36	1.00
Share of energy expenditure in total expenditure	0.00	0.06	0,09	0.11	0.15	0.75
Share of combined food and energy expenditure in total expenditure	0.00	0.28	0.39	0.40	0.51	1.00

Source: author's work based on data from the Household Budget Survey 2021.

For a deeper analysis of qualitative variables, including X_3 (subjective energy poverty), X_4 (location), X_5 (socio-economic group), and X_6 (household composition), the frequencies of all households participating in the study were calculated and presented in charts based on each variable.

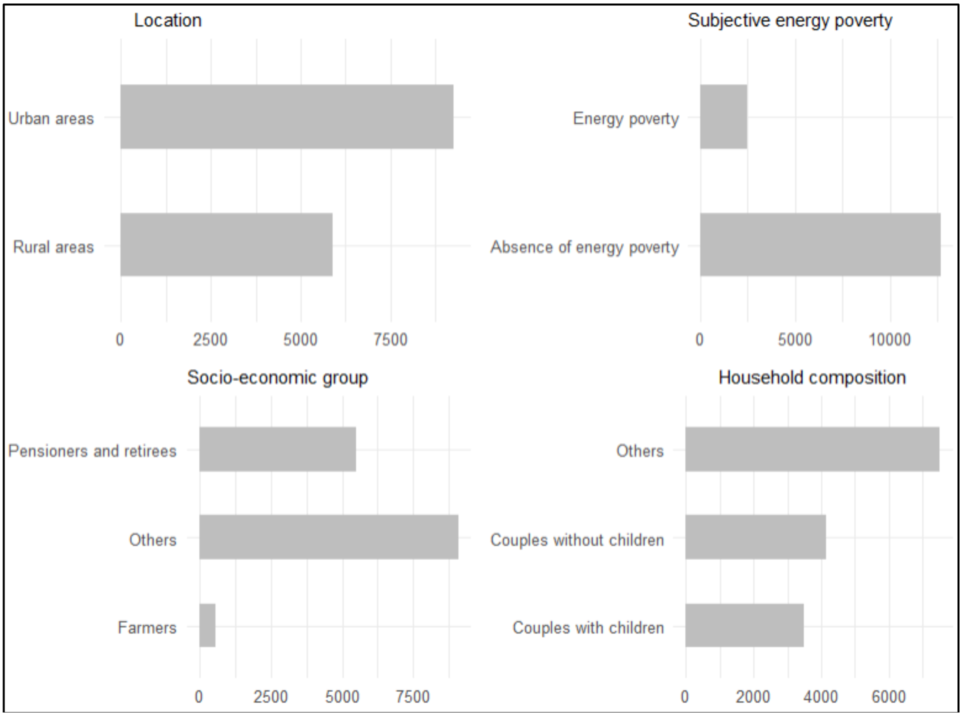
Figure 1 illustrates, among other things, the number of households in specific types of locations. There are the following categories of towns and cities: small towns with up to 20,000 inhabitants, medium-sized towns ranging between 21,000 and 99,000 inhabitants as well as between 100,000 and 500,000 inhabitants, and large urban agglomerations with populations exceeding 500,000. Most respondents lived in urban areas (9,270 households), while about 3,000 fewer resided in rural areas (5,877 households).

Figure 1 also shows the number of energy-poor and non-energy-poor households. The criteria for belonging to either group are based on the aforementioned subjective material assessment of individual households. The vast majority of respondents did not fall into the energy-poor category. Only about 17% of households rated themselves as energy-poor.

When analysing socio-economic groups, it can be seen that the largest group consists of members of 'other households', which are the households of people in employment, the self-employed, and people relying on non-earned income sources. The second largest group are the households of retirees and pensioners, and the smallest group consists of households of farmers.

In terms of household composition, the largest group as well is called 'other households'. This category consists of single individuals with dependent children and single-person households. Meanwhile, the number of couples without children is slightly larger than that of couples with children.

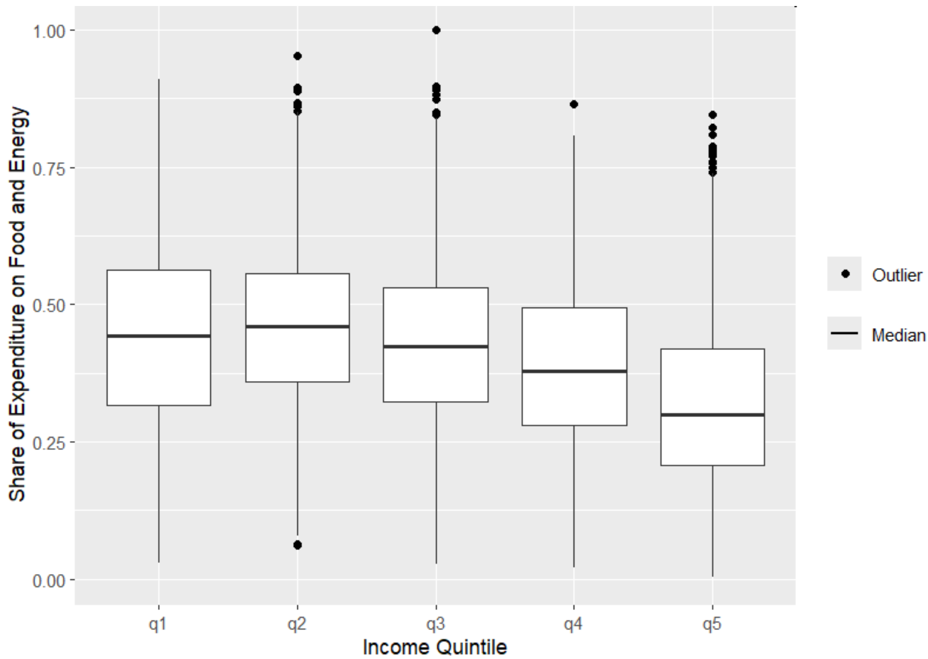
Figure 1. The number of all households participating in the study



Source: author's work based on data from the Household Budget Survey 2021.

Figure 2 illustrates the level of spending on food and energy of Polish households. From the second income quintile onwards, i.e. as the income quintile increases, the share of spending on food and energy in the total expenditure decreases. This suggests that wealthier families allocate a smaller percentage of their budget to basic needs, and a larger percentage to entertainment, travel, or savings.

Figure 2. The share of spending on food and energy in total expenditure by income quintile



Source: author's work based on data from the Household Budget Survey 2021.

4.2. Tobit model

Variables limited in their range often appear in statistical research. Examples include truncated, censored or binary variables. The appropriate tool for describing these is the Tobit model (Maddala, 1983). The standard Tobit model for a discrete-continuous variable y_i can take the form of (Tobin, 1958):

$$\begin{cases} y_i^* \; if \; y_i^* > \gamma \\ 0 \; if \; y_i^* \leq \gamma \end{cases}, \tag{1a}$$

$$y_i^* = \alpha + X_i\beta + \varepsilon_i, \tag{1b}$$

where y_i^* is a latent response variable, γ is a nonstochastic constant, β is a vector of parameters for this model, and X_i is a vector of explanatory variables, $\varepsilon_i \sim N(0, \sigma^2)$.

When analysing economic data, the value of γ is often unobservable. It is then assumed to be 0 (Carson & Sun, 2007). The Tobit model then takes the form:

$$\begin{cases} y_i^* \; if \; y_i^* > 0 \\ 0 \; if \; y_i^* \leq 0 \end{cases}, \tag{2a}$$

$$y_i^* = \alpha + X_i\beta. \tag{2b}$$

In the literature, the Tobit model and its generalisations are usually considered under the assumption of a normal distribution for the error term ε_t (Jeong & Jeong, 2015). In this case, the maximum likelihood estimation (MLE) method is natural for estimating this model, as it ensures the asymptotic normality of the parameter estimates.

The assumption of a normal distribution for the error term ε_t was not met, despite numerous attempts to transform the model. This could also be attributed to the sample size (15,147 observations). As a result, we can say that the model's efficiency is slightly reduced.

5. Empirical results

5.1. Tobit model

To understand which factors influence the share of expenditure on food and energy in the total expenditure of Polish households, Tobit models were estimated. Identifying the determinants of the share of food and energy expenditure in the total expenditure is an important element of studying household consumption behaviours. This is particularly significant in the context of the current shocks on energy commodity markets. Additionally, it is possible to identify households struggling with the 'heat or eat' dilemma. The obtained results can thus help guide social and economic policies addressing the most vulnerable households and minimise the risk poverty will spread and deepen among Polish families.

To estimate the Tobit models, six characteristics of Polish households were used: the number of household members, the logarithm of disposable income, location, belonging to a particular socio-economic group, household composition and the occurrence or not of energy poverty. Three exogenous variables were used, namely the share of food expenditure, the share of energy expenditure, and the share of combined food and energy expenditure in the total expenditure. Thus, three different Tobit models were estimated and compared.

During the analysis of qualitative variables, reference values were chosen as benchmarks for interpreting the results. These were: socio-economic group – others, location – rural area, household composition – others, and energy poverty – none.

Table 4. Estimated parameters of Tobit models for three exogenous variables

Description	Exogenous variable[a]		
	Share of food expenditure	Share of energy expenditure	Share of combined food and energy expenditure
Intercept	0.650***	0.218**	0.870***
Number of household members	0.016***	−0.001*	0.015***
The logarithm of disposable income	−0.046***	−0.012***	−0.058***
Energy poverty	0.007**	0.014***	0.021***
Location (size)	−0.039***	−0.008***	−0.048***
Farmers	−0.074***	−0.027***	−0.100***
Pensioners	0.021***	0.026***	0.046***
Married couples without children	0.014***	−0.005***	0.009***
Married couples with children	−0.018***	−0.021***	−0.039***

a *** – significance at a 1% level, ** – significance at a 5% level, * – significance at a 10% level.
Source: summary of the results generated in the Gretl.

The analysis of the first variable shows that as the number of household members increases by one, the predicted share of food expenditure and the combined food and energy expenditure increases by 0.016 and 0.015, respectively. This result is also confirmed by the literature (see García & Grande, 2010). On the other hand, the share of energy expenditure in the total expenditure decreases by 0.001. This result is intuitive, because energy expenditure is divided among the household members, so the more people in a household, the smaller the percentage burden.

The logarithm of disposable household income can be described as a reducing factor across all the models. As income increases, the predicted values of the three dependent variables decrease. This was also confirmed in section 4.1, where the share of food and energy expenditure in the total expenditure was changing across income quintiles. The interpretation of Figure 2 is analogous to the obtained parameter estimates. This result is consistent with Engel's law, as described in other studies (Sekhampu, 2012).

The variable related to energy poverty has a different interpretation. The predicted values of the three dependent variables are higher for households affected by energy poverty than for households not suffering from it. This interpretation is consistent with the literature review. Households experiencing energy poverty are typically classified as low-income households, which is why their shares of food expenditure, energy expenditure, and combined food and energy expenditure in the household's total spending are relatively high.

Analysing the next variable, we can observe that the predicted shares of food expenditure, energy expenditure, and the combined food and energy expenditure in the total spending of households in cities are lower by 0.039, 0.008, and 0.048, respectively, than those of households in rural areas. This may be due to the fact that urban residents are generally wealthier, and thus allocate a part of their resources to other needs. Additionally, they may have different consumption preferences, such as eating out more frequently, which leads to doing less food shopping. The results of other studies (Borowska et al., 2020) also showed that food expenditure of urban households is proportionally lower than that of rural households.

As regards farmer households, there is a similar trend. The predicted values of the three above-mentioned shares of expenditure in farmer households' total expenditure are lower by 0.074, 0.027, and 0.100 than those of other social groups (people in employment, the self-employed, and those whose income comes from non-labor sources). This is likely due to the fact that farmers often use their own food products and may allocate their financial resources to household needs other than food.

In contrast, the estimated parameters for the variable that describes belonging to the social group of pensioners and retirees differ from those for the variable that describes belonging to the group of farmers. The predicted shares of food expenditure, energy expenditure, and the combined food and energy expenditure in a pensioner or retiree household's total spending are higher than in the case of other social groups. This is also confirmed by Utzig (2016).

The predicted values of the first dependent variable are higher for couples without children by 0.014, and the predicted values of the second dependent variable are lower by 0.005 than those for single-person households and single parents with children. This may be due to the fact that couples without children travel more frequently than single people, and thus consume less energy. On the other hand, higher shares of food expenditure in the total spending of couples without children may result from the fact they have a smaller need to save, therefore feel less restricted in food shopping.

The predicted shares of food, energy, and combined food and energy expenditure in the total spending of married couples with children are lower by 0.018, 0.021, and 0.039, respectively, than those of single-person households and single parents with children. The surveyed married couples are relatively wealthy, so this result is not surprising. It might also be related to Poland's social policy, which provides cash benefits to families with children. This finding is also consistent with the literature (Grzega, 2015).

Most of the estimated parameters indicate that the study is reliable, as the obtained results and interpretations are similar to what earlier research showed, and they might to some extent be verified by life experience and common sense.

5.2. Tobit model with interactions

For a more detailed analysis of Polish energy-poor households, several Tobit models with interactions were estimated. The same explanatory and exogenous variables were used as in the previous model (Table 4). The reference values remained unchanged. The variables describing the logarithm of disposable income and the number of persons in the household are included in each model. Other models are based on the characteristics of the location (class), belonging to a particular social group and household composition. The last three models include all the above factors and their interactions with the variable describing energy poverty.

The estimated parameters of the first three Tobit models with interactions are presented in Table 5. Energy-poor households in cities incur proportionally lower expenditure on food and food and energy combined, but higher expenditure on energy alone than families living in rural areas. This is a slightly surprising result. One would expect that there are more houses in rural areas and more blocks of flats in cities, which seem to incur lower energy costs, but the opposite is true. Inhabitants of urban areas often live in blocks of flats, which involves fixed expenses on energy and a limited capability for energy-saving solutions. In contrast, households in rural areas can reduce energy costs by using solid fuels, such as wood for heating. This situation is described by the term 'hidden energy poverty', which refers to extremely low share of energy expenditure in a household's total spending (Eisfeld & Seebauer, 2022).

Table 5. The estimated parameters of Tobit models with interactions for household location for three exogenous variables

Description	Exogenous variable[a]		
	Share of food expenditure	Share of energy expenditure	Share of combined food and energy expenditure
Intercept	0.668***	0.265***	0.934***
Number of household members	0.008***	–0.008***	–0.001
The logarithm of disposable income	–0.030***	–0.015***	–0.061***
Energy poverty	0.027***	0.011***	0.038***
Location (size)	–0.030***	–0.010***	–0.041***
Energy poverty*Location (size)	–0.030***	0.013***	–0.017**

a As in Table 4.
Source: summary of the results generated in the Gretl.

Table 6 presents the parameter estimates for the Tobit model with interactions for variables related to the social group the members of the household belong to. The share of expenditure on food and the share of the combined expenditure on food and energy in the total spending of energy-poor households of retirees and pensioners are lower than those of other social groups. In contrast, the occurrence of energy poverty among farmers increases their predicted shares of food expenditure in the total spending, at the same time decreasing their predicted share of energy expenditure in the total spending (compared to other social groups). This observed lower energy expenditure may result, as mentioned before, from using the available solid fuels (e.g. wood) to heat their households, in order to minimise their energy costs.

Table 6. The estimated parameters of Tobit models with interactions for socio-economic group for three exogenous variables

Description	Exogenous variable[a]		
	Share of food expenditure	Share of energy expenditure	Share of combined food and energy expenditure
Intercept	0.624***	0.215***	0.841***
Number of household members	0.017***	–0.003***	0.014***
The logarithm of disposable income	–0.047***	–0.013***	–0.060***
Energy poverty	0.012***	0.017***	0.030***
Farmers	–0.056***	–0.016***	–0.071***
Pensioners	0.030***	0.029***	0.059***
Energy poverty*Farmers	0.043***	–0.026**	0.016
Energy poverty*Pensioners	–0.012**	–0.001	–0.013**

a As in Table 4.

Source: summary of the results generated in the Gretl.

Table 7 presents the estimated parameters of Tobit models with interactions for the composition of a household and energy poverty. In this case, the estimated parameters with interactions turned out to be statistically insignificant, which means that the impact of these variables on the share in expenditure cannot be fully confirmed in the studied sample. Nevertheless, if we were to interpret the results despite the lack of statistical significance, we would be able to observe that households of married couples with children who experience energy poverty had lower predicted shares of energy and food expenditure in their total spending than single-person households or single parents with dependent children. This may be related to the effect of scale, i.e. decreasing unit costs as the number of household members increases, and sharing costs (if both parents are employed).

Table 7. The estimated parameters of Tobit models with interactions for household composition for the three exogenous variables

Description	Exogenous variable[a]		
	Share of food expenditure	Share of energy expenditure	Share of food and energy expenditure
Intercept	0.668***	0.257***	0.927***
Number of household members	0.017***	−0.003***	0.015***
The logarithm of disposable income	−0.051***	−0.016***	−0.067***
Energy poverty	0.010***	0.019***	0.030***
Married couples without children	0.019***	−0.000	0.020**
Married couples with children	−0.025***	−0.026***	−0.050***
Energy poverty* Married couples without children	−0.003	−0.006	−0.010
Energy poverty* Married couples with children	−0.004	−0.006	−0.001

a As in Table 4.

Source: summary of the results generated in the Gretl.

Table 8 presents the parameter estimates for Tobit models with interactions for all the variables used in the previous models. The estimated parameters of the interaction variable describing energy-poor households in urban areas are very similar to those obtained for the first model (Table 5). The direction of the impact of explanatory variables on dependent variables is the same in both models. A similar situation can be observed for the interaction of energy poverty with farmers (Table 6). In contrast to previous models, the remaining estimated interactions were statistically insignificant.

Table 8. The estimated parameters of Tobit models with interactions for three exogenous variables

Description	Exogenous variable[a]		
	Share of food expenditure	Share of energy expenditure	Share of combined food and energy expenditure
Intercept	0.644***	0.219***	0.866***
Number of household members	0.016***	−0.001*	0.015***
The logarithm of disposable income	−0.046***	−0.012***	−0.058***
Energy poverty	0.025***	0.010**	0.034***
Location (size)	−0.035***	−0.010***	−0.046***
Farmers	−0.076***	−0.025***	−0.101***
Pensioners	0.022***	0.025***	0.048***
Married couples without children	0.014***	−0.005**	−0.009
Married couples with children	−0.018***	−0.021***	−0.038***
Energy poverty*Location (size)	−0.025***	0.011***	−0.014**
Energy poverty*Farmers	0.029*	−0.018	0.010
Energy poverty* Pensioners	−0.006	$-2.810 \cdot 10^{-5}$	−0.006
Energy poverty* Married couples without children	−0.005	−0.004	−0.010
Energy poverty* Married couples with children	−0.000	−0.002	−0.002

a As in Table 4.

Source: summary of the results generated in the Gretl.

6. Conclusions

The aim of this study was to identify the socio-economic determinants of how big the share of expenditure on food and energy in households' total spending is, as well as to examine how energy poverty affects the level of this expenditure. All the variables proposed in the analysis, namely the size of a household, the logarithm of the household's disposable income, the occurrence or not of energy poverty, the composition of a household, as well as belonging to a particular socio-economic group (in our case pensioners and farmers) turned out to be statistically significant. This indicates that the share of expenditure on food and energy in a household's total spending depends on a range of factors, thus attesting to the complexity of the problem under study.

The study's objective was successfully verified in the course of our analysis. The constructed models indicated a decrease in the ratio of expenditure on food to the household's total expenditure as its income was increasing. As mentioned before, this result is not surprising, as wealthier households tend to allocate some of their income to needs other than basic, such as culture, entertainment or travel. Therefore, the share of food expenditure in their total spending is relatively low. Another finding is that households located in rural areas spent proportionally more of their income on food than those in urban areas. This probably results from the characteristics of affluent urban households, which typically devote some part of their income to needs other than basic, e.g. their members eat out more frequently. An interesting outcome was the situation where the share of energy expenditure in a household's total expenditure was higher for energy-poor households in cities than in rural areas. This, as already explained, might be because city residents often live in blocks of flats, where energy costs are fixed – inhabitants cannot implement their own energy-efficient solutions. In contrast, rural households can reduce energy costs by using solid fuels to heat their homes affordably.

For a deeper analysis of energy-poor households, Tobit models with interactions were used. Compared to the results yielded by previous models, not all parameter estimates turned out to be statistically significant. The obtained models showed that experiencing energy poverty by farmers increases the predicted share of expenditure on food in their total spending, while for other social groups, i.e. people in employment, the self-employed and people relying on non-earned income, it decreased the share of expenditure on energy compared to other social groups. On the other hand, the expenditure on food and both food and energy combined of energy-poor families living in cities turned out to be lower than the analogous expenditure of energy-poor families living in rural areas, but higher than expenditure on energy alone of those latter families. Married couples struggling with energy poverty, both with and without children, tend to spend proportionally less on food and energy than single-person households or single parents with dependents.

The results obtained in this study expand our knowledge on consumer behaviour by providing valuable insights into how various socio-economic factors affect the share of households' expenditure on food and energy in their total spending. Our results are generally compliant with other relevant research. Both the literature and our study indicate the share of households' expenditure on food and energy in their total spending differs across social groups, locations of households and their types. Additionally, the estimates regarding the impact of disposable income on food expenditure show consistency with Engel's Law, which supports economic theories concerning spending in relation to income.

The literature often highlights the general impact of energy poverty on consumption expenditure. The results of our analysis focus on the share of households' expenditure on food and energy in their total expenditure, demonstrating that the former is determined to a large extent by the occurrence or not of energy poverty, which also correlates with the socio-economic characteristics of households. Notably, we demonstrated that households experiencing energy poverty in urban areas spend more on energy than those in rural areas.

The results obtained in our study can be used as guidelines for developing social policies addressed to excluded groups. Our findings might also serve as a foundation for further research aimed at creating strategies to prevent the negative consequences of state-driven crises.

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Report from the 33rd Scientific Conference of the Classification and Data Analysis Section of the Polish Statistical Association

Andrzej Dudek,[a] Paweł Lula,[b] Barbara Pawełek[c]

The 33rd Scientific Conference of the Classification and Data Analysis Section (SKAD) of the Polish Statistical Association (PSA) was held on 5th–6th June 2024, in Kraków, Poland. The conference was organised by SKAD and the Krakow University of Economics. Basic information about the conference is available at: https://skad2024.uek.krakow.pl/.

The organising committee consisted of Prof. Paweł Lula from Krakow University of Economics (Chairperson) and Małgorzata Ćwiek, PhD, Michał Widlak, PhD, Aleksandra Bojda, MSc, and Katarzyna Wójcik, MSc.

The following topics were addressed during the conference:

- theoretical aspects, i.e. taxonomy, graphical methods, discriminant analysis, linear ordering methods, multivariate statistical analysis, methods of analysing continuous and discrete variables, symbolic data analysis, machine learning methods;
- applications, namely financial data analysis, marketing data analysis, spatial data analysis, computer application of statistical methods and other fields using data analysis, like medicine, psychology, archaeology, etc.

The main objective of the SKAD conference was to present the current research on theoretical and applied aspects of data classification and analysis and create a platform for exchanging ideas relating to these issues. The conference, held annually, provides an opportunity for the participants to present and promote state-of-the-art research, and indicates possible development directions.

[a] Wroclaw University of Economics and Business, Faculty of Economics and Finance, Department of Econometrics and Computer Science, ul. Komandorska 118/120, 53–345 Wrocław, Poland, e-mail: andrzej.dudek@ue.wroc.pl, ORCID: https://orcid.org/0000-0002-4943-8703.

[b] Krakow University of Economics, College of Management and Quality Sciences, Department of Computational Systems, ul. Rakowicka 27, 31–510 Kraków, Poland, e-mail: pawel.lula@uek.krakow.pl, ORCID: https://orcid.org/0000-0003-2057-7299.

[c] Krakow University of Economics, College of Economics, Finance and Law, Department of Statistics, ul. Rakowicka 27, 31–510 Kraków, Poland, e-mail: barbara.pawelek@uek.krakow.pl, ORCID: https://orcid.org/0000-0002-9589-6043.

The conference gathered 44 participants. This group consisted of faculty members or doctoral students of several universities and institutions, namely the University of Bologna, Gdańsk University of Technology, Warsaw University of Life Sciences, University of Economics in Katowice, Krakow University of Economics, Poznań University of Economics and Business, Wroclaw University of Economics and Business, the University of Gdańsk, Adam Mickiewicz University in Poznań, University of Lodz, the University of Szczecin, the Statistical Office in Poznań, West Pomeranian University of Technology in Szczecin and Wroclaw Medical University, and representatives of Docmatic sp. z o.o. (limited liability company).

24 presentations introducing research results on the theory and application of the classification and data analysis were delivered in the course of three plenary sessions, four parallel sessions and a poster session. The sessions were chaired by Andrzej Dudek, Marek Walesiak, Krzysztof Jajuga, Józef Pociecha, Grażyna Dehnel and Krzysztof Najman.

Below is the list of all papers presented during the conference:

- Angela Montanari, *Perturb and Conquer. How Classification Can Benefit from Data Perturbation*;
- Marek Walesiak, Grażyna Dehnel, Andrzej Dudek, *Visualization of linear ordering results using multidimensional scaling – problems and research review*;
- Krzysztof Najman, Kamila Migdał Najman, *Are the AI code of ethics and AI Act sufficient signposts for a data analyst?*;
- Beata Bieszk-Stolorz, Krzysztof Dmytrów, Ewa Frąckiewicz, *Multidimensional analysis of the development of the silver economy in EU countries in 2009–2021*;
- Dorota Rozmus, *The use of combined forecasts as a tool for assessing the impact of the COVID pandemic on the Polish economy with a focus on the manufacturing section and the Silesian region*;
- Jacek Batóg, Iwona Foryś, *Comparative analysis of the effect of reference market distance on the "noise level – unit price of real estate" relationship in the surroundings of Polish airports*;
- Dominik Krężołek, *GARCH class models with kernel error distribution in volatility and risk analysis for selected European stock market indices in 2015–2023*;
- Joanna Landmesser-Rusek, *Granger causality networks for the foreign exchange market*;
- Marta Kuc-Czarnecka, Iwona Markowicz, Agnieszka Sompolska-Rzechuła, *Patterns of growth convergence for selected environmental sustainability goals*;
- Karolina Tądel, Andrzej Dudek, Iwona Bil-Lula, *Real-time data in medicine – comparison of clinical decision support models*;

- Wojciech Łukaszonek, Marcin Szymkowiak, Waldemar Wołyński, *Classification of local labour markets in the Wielkopolska province based on spatial-temporal principal component analysis*;
- Jacek Białek, Dagmara Oprych-Franków, *Downsizing – automatic detection and its impact on inflation*;
- Barbara Batóg, Jacek Batóg, *Comparative analysis of the research and teaching potential of Polish universities in 2019–2022*;
- Jadwiga Kostrzewska, Maciej Kostrzewski, *Energy mix and electricity price volatility*;
- Małgorzata Ćwiek, Paweł Ulman, Maria Sadko, *Housing conditions in Central and Eastern European countries*;
- Marcin Salamaga, *Taxonomic analysis of innovation diffusion processes in renewable energy sources*;
- Łukasz Malicki, *Application of classical and large language models in the analysis of business documents: Perspectives, methods and implications*;
- Cinzia Viroli, Edoardo Redivo, *Multivariate Analysis and Classification with the Integrated Rank-Weighted Depth*;
- Andrzej Sokołowski, Małgorzata Markowska, *In Search of Another Measure of Variability*;
- Anna Majdzińska, *Demographic and socio-economic determinants of population change in Poland (regional approach)*;
- Artur Mikulec, *Persistence of enterprises in the Łódź province – results of indicator analysis*;
- Natalia Pawelec, *Comparison of Bennet and Montgomery indicators using scanned data*;
- Marcin Pełka, *A multi-model approach of symbolic data in detecting credit card fraud*;
- Kamila Trzcińska, Elżbieta Zalewska, *Comparison of income distributions and the economic situation of farmer households in selected EU and US countries*.

The members of SKAD held an annual meeting on the first day of the conference. The meeting was chaired by Andrzej Dudek, President of SKAD, and its agenda featured:

- report on the SKAD activities;
- information on the planned domestic and international conferences related to data analysis;
- organisation of SKAD conferences in 2025 and 2026;
- elections to the SKAD Council for the term of 2025–2026;
- other issues.

A report on the activities undertaken by SKAD was presented by the Secretary of the SKAD Council, Barbara Pawełek, PhD, DSc, Association Professor at the Krakow University of Economics. Currently, according to the report, SKAD has 234 members, and any by-laws and membership applications are available on the SKAD website. Then, a minute of silence was observed in memory of the members of SKAD who had recently passed away.

In the following part of the meeting, two pieces of information were announced – that the report from the SKAD conference (held in Katowice on 19th–20th September 2023) could be found in issue 3/2023 of *Przegląd Statystyczny. Statistical Review*, and that Anna Denkowska, PhD (Krakow University of Economics) participated in the IV International School on Classification and Data Analysis, held on 19th–23rd February 2024 in Rome. That edition of the School was entitled 'Statistical Methods for Unsupervised and Supervised Learning with Dimensionality Reduction'.

The following conferences took place in 2024: IFCS 2024 (15th–19th July 2024, San Jose, Costa Rica), ECDA 2024 (9th–11th September 2024, Sopot, Poland), GPSDAA 2024 (11th September 2024, Sopot, Poland), and the 42nd International Conference on Multivariate Statistical Analysis (4th–6th November 2024, Łódź, Poland). Two conferences are planned for 2025: the 18th Aleksander Zeliaś International Conference on the Modelling and Forecasting of Socio-Economic Phenomena (12th–15th May 2025, Zakopane, Poland) and CLADAG 2025 (8th–10th September 2025, Naples, Italy).

The participants then went on to discuss the schedule for the upcoming SKAD conferences. Andrzej Dudek of the Wroclaw University of Economics and Business declared that the University would host the conference in 2025.

Subsequently, the election of the members of the SKAD Council for the 2025–2026 term was held. As a result of a secret ballot, the following members were selected: Barbara Pawełek, Grażyna Dehnel, Andrzej Dudek, Krzysztof Jajuga, Joanna Landmesser-Rusek, Paweł Lula, Krzysztof Najman and Marek Walesiak.

Then, the newly-elected SKAD Council held its first meeting, during which its board was selected. Andrzej Dudek was appointed Chairman of the Council, Paweł Lula Vice-Chairman of the Council, Barbara Pawełek the Secretary of the Council, and Grażyna Dehnel, Krzysztof Jajuga, Joanna Landmesser-Rusek, Krzysztof Najman and Marek Walesiak were named the Members of the Council.

Prof. Andrzej Dudek informed the members about the composition of the SKAD Council for the 2025–2026 term and about the possibility of publishing the presented papers. He invited the members to the next SKAD conference to be held in Wrocław.