SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2025
ORGANIZATION AND MANAGEMENT SERIES NO. 229

ARTIFICIAL INTELLIGENCE AND THE SUSTAINABLE CITY: HOW TECHNOLOGY TRANSFORMS URBAN FUTURES

Joanna SZAREK-ORLECKA[1*], Paulina CADER[2]

[1] University of Agriculture in Cracow; joanna.szarek@urk.edu.pl, ORCID: 0000-0001-9885-8424
[2] University of Agriculture in Cracow; paulina.cader@urk.edu.pl, ORCID: 0009-0009-6954-8975
* Correspondence author

Purpose: The purpose of this article is to study the role of technology in key areas of sustainable cities, such as infrastructure and transportation management, waste management, energy consumption or quality of life of residents. In addition, a ranking of selected European cities was constructed in terms of the adaptive potential of artificial intelligence in the perspective of sustainable urban development.
Design/methodology/approach: The research used a taxonomic method, a comparative method and a literature study.
Findings: The greatest potential for adapting strategic solutions using artificial intelligence to create smart cities in light of achieving the Sustainable Development Goals, among the cities accepted for analysis, was demonstrated by Paris, where for almost a decade now local authorities have focused on implementing the city as a platform model.
Originality/value: The article addresses current trends in regional development, in particular, the development of the smart city, taking into account the challenges of implementing artificial intelligence. The research is focused on the possibilities of using new technologies in the adaptation of urban communities to such phenomena as an aging population, or the implementation of sustainable development strategies. This is an important and innovative approach in regional research.
Keywords: artificial intelligence, sustainability, smart cities, urban technologies.
Category of the paper: Research paper.

1. Introduction

Progressive urbanization, urban population growth, and the growing challenges of climate change are making cities prime areas for implementing innovative solutions to support the idea of sustainable development (Niedziela-Wawrzyniak, 2023). Today's socio-economic and environmental challenges call for modern, open-ended governance models that will enable urban residents to not only maintain their current standard of living, but also raise it while maintaining environmental sustainability. One of the more promising tools in this regard is artificial intelligence (AI), which offers advanced capabilities for data processing, process automation and efficient management of urban resources (Blicharz, 2023).

Despite the growing interest in smart cities, the role of artificial intelligence in the implementation of sustainable urban development strategies is still under-researched. There is a lack of in-depth and comprehensive studies to assess to what extent European cities are actually implementing AI-based solutions in their development policies, and what real impact these technologies have on improving the quality of life of residents, the efficiency of resource management and reducing negative environmental impacts.

The purpose of the article is to study the role of technology in key areas of sustainable cities. Referring to the main objective, a ranking of selected European cities in terms of the adaptive potential of artificial intelligence in the perspective of sustainable urban development was constructed. The analysis of this issue prompts the key research questions: To what extent are European cities using AI to support sustainable development? Which areas of city functioning are most susceptible to transformation through this technology? In which areas can the development of artificial intelligence positively affect regional development? With regard to the research questions, a research hypothesis was formulated: artificial intelligence and new technologies are leveling social problems in smart cities.

The structure of the article includes a review of the literature on sustainable cities and the role of artificial intelligence in their transformation, the methodology of the study based on taxonomic and comparative analysis, the presentation of the results, and conclusions on the role of artificial intelligence in creating more sustainable urban spaces. The issue addressed not only answers the existing research gap, but also brings new value by proposing to local authorities the adaptation of AI in the context of urban sustainability and current socio-regional challenges. The study focuses on the role of technology in key areas of sustainable city operations, such as infrastructure and transportation management, education or quality of life for residents.

2. The importance of artificial intelligence in shaping smart cities

2.1. Artificial intelligence in the context of sustainable urban development

The origins of the development of artificial intelligence can be traced back to the 1950s, when Alan Mathison Turing published a landmark article entitled "Computer Machinery and Intelligence" in the pages of the Oxford journal Mind. At the very beginning of his paper, Turing offered readers a reflection on the fundamental question: "Can machines think?", which has become one of the key issues in the further development of AI research (Rashid et al., 2024).

Artificial intelligence is present today in almost all areas of life. Its capabilities are used in business, IT, security systems, agriculture, as well as in everyday activities, among others. Such a wide application confirms its versatility, innovative nature and rapid pace of development. AI's particularly great potential is evident in working with huge data sets from the Internet, as well as in tasks requiring creativity or evaluation and analysis (Szews, 2024). AI is particularly effective in analyzing large data sets generated in digital environments, as well as in tasks requiring creativity, evaluation and decision-making (Ljepava, 2022). Artificial intelligence is increasingly applied in many spheres of socio-economic life. It is being used as a key tool in the strategic planning of manufacturing enterprises, assisting supply chain management and supporting managers at various decision-making levels. Increasingly, cities and regions are also implementing AI-based solutions to improve the management of daily processes and increase the efficiency of public administration (Czyzewska-Misztal, 2024).

In the context of developing sustainable cities, artificial intelligence is becoming an increasingly important tool to support both urban planning and urban infrastructure management. Its use can significantly improve decision-making processes, increase the efficiency of managing urban resources and services, and improve the quality of life of residents. AI can play a key role in creating intelligent transportation systems, monitoring air pollution, managing energy, and responding to social needs in real time (Blicharz, 2023).

Sustainable development is based on three key foundations: meeting human needs, ensuring social justice, and taking into account environmental constraints. This means consciously and responsibly shaping the relationship between economic development, care for the environment - especially the natural environment - and the realization of various human needs, which largely affect the quality of life (Mierzejewska, 2015).

2.2. Smart city technologies and the integration of AI into urban policies

The term “Smart City” has begun to reflect the key needs of residents of modern cities. The term is most often associated with openness to modern solutions, the ability to adapt dynamically, and the use of innovative technologies to improve the quality of life in urban spaces (Czemiel-Grzybowska, 2023).

Today's cities are facing increasingly complex challenges, such as economic crises, climate change, aging populations, infrastructure overload, the emergence of online retail, and the need to ensure a high quality of life for residents (Podgórniak-Krzykacz, Przywojska, 2023). In response to these problems, the smart city concept, which aims to create more efficient, sustainable and crisis-resilient urban structures by integrating modern technologies, including artificial intelligence (AI), into urban policies, is gaining importance (Widuch, 2022).

The term smart city can be defined in different ways, but all theoretical approaches emphasize that these are cities that use information and communication technologies (ICT) to solve social and development problems. A smart city is one that simultaneously develops modern technological infrastructure and invests in human and social capital, offering residents access to e-services and digital solutions to support daily life (Legutko-Kobus, 2021). Integrating AI with city policies is becoming the foundation of modern governance - supporting urban planning, transportation, waste management, environmental protection, as well as security and civic participation (Lee and Lee, 2015).

In the context of integrating AI into urban policies, it is worth noting selected European cities that represent different levels of sophistication and adaptation strategies. In cities such as Paris, Madrid, Rome, Brussels, Budapest, Helsinki, Riga, Vilnius and Tallinn, there is a noticeable increase in the importance of AI as a tool to support the implementation of smart city strategies. For example:

- Paris is investing in AI-based urban platforms to manage mobility, air quality and energy, while developing a “city as a platform” model (Arduin et al., 2016).
- Madrid is pursuing a strategy of advanced digital transformation of urban space, based on the integrated development of social, environmental and economic components. A key element of this strategy is the use of real-time data to increase the efficiency of public services and improve emergency management systems (Orejon-Sanchez et al., 2022).
- Budapest is focusing its efforts on developing a modern transportation infrastructure, using digital technologies to improve the city's operations. The city government is implementing public transportation management systems that rely on data analysis to enable more efficient route planning and optimize the operation of public transportation and city services (Hamadneh, Jaber, 2023).
- Helsinki is developing the “City as a Service” concept, which aims to create citizen-centered city services. Here, AI is supporting urban planning, transportation management, digital healthcare and predicting demand for public services, among other things. The city also relies on transparency - residents have access to data on the operation of AI-based systems, which increases public trust and promotes acceptance of innovations (Anttiroiko, Sahamies, 2022).

However, the implementation of AI in urban policies is not a uniform process - it depends on many factors, such as the level of digital sophistication, availability of data, competence of officials, infrastructure and the organizational culture of the administration. Equally important are mechanisms for collaboration with the private sector and academia to create innovation ecosystems.

3. Methodology

The study consisted in developing a ranking of selected European cities on the basis of characteristics describing the level of regional development. The basic element of the analysis was the selection of a group of diagnostic variables that best reflect the degree of development of cities. The initial set of diagnostic characteristics was selected from available statistical data on the basis of a substantive criterion. The components of the substantive criterion were the purpose and subject of the study, as well as the time frame in which the study was conducted (Szarek, 2021). In addition, the selection of variables was determined by the availability and completeness of empirical data, which were obtained from the databases of the statistical office of the European Union (Eurostat). As a result, ten diagnostic variables of the set of diagnostic characteristics were qualified for the study. All of the variables selected for the study were identified as stimulants. Stimulants are characteristics that have a positive impact on the analyzed area. The first step in the calculation was the estimation of Pearson's linear correlation coefficient. Pearson's linear correlation coefficient takes values in the range of [-1, 1].

The closer this value is to one, the stronger the relationship is. In the literature, it is assumed that $r_{xy} < 0.3 -$ designates an insignificant correlation; $0.3 < r_{xy} \leq 0.5 -$ average correlation; $r_{xy} > 0.5 -$ clear correlation. The Pearson's linear correlation coefficient was estimated using the following formula:

$$r_{xy} = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{[n\sum X^2 - (\sum X)^2] * [n\sum Y^2 - (\sum Y)^2]}} \tag{1}$$

where:

r_{xy}– Pearson's linear correlation coefficient,

n – number of elements in the set,

X – explanatory variable,

Y – explained variable (Chudy-Hyski, 2006).

The criterion used for the classification of features was the value of the sum of modules of the correlation coefficient number for individual variables (s.m.), and namely {s.m. < 8} was the determining condition for qualification of diagnostic features for creation of the ranking.

The next criterion for the selection of diagnostic variables was their sufficiently high degree of variation. The degree of differentiation of individual characteristics was estimated on the basis of the coefficient of variation. It was established that the value of the coefficient of variation of the studied diagnostic variables should exceed (>10%), which means that the trait indicates significant variation (Szarek-Orlecka, 2025).

Continuing with the analysis of selected diagnostic variables, standardization was performed using the formula:

$$z_{it} = \frac{z_{it-}\,\bar{x_\iota}}{s_i} \tag{2}$$

where:

$$\bar{x_\iota} = \frac{1}{n}\sum_{t=1}^{n} x_{it} \tag{3}$$

$$S_i = \left[\frac{1}{n}\sum_{i=1}^{n}(x_{it} - x_i)^2\right]^{0,5} \tag{4}$$

where: z_{it} – standardized value of the diagnostic feature x_i over time t (Murawska, 2010).

Using estimated standardized values of the diagnostic features, a index of standardized sums for individual regions was calculated according to the formula:

$$Z'_{it} = \frac{(\sum z_{it})}{n} \tag{5}$$

where: n – number of diagnostic variables.

The natural breaks method divides into five classes, where:

- class 1: $Z'_{it} > 2.00$,
- class 2: $2.00 < Z'_{it} < 0.00$,
- class 3: $0.00 < Z'_{it} < -0.5$,
- class 4: $-0.50 < Z'_{it} < -0.80$
- class 5: $-0.80 < Z'_{it} < -1.00$.

The survey made it possible to rank selected European cities based on their level of regional development. An important element of the study was the adequate selection of diagnostic variables that met statistical, substantive and data availability criteria. Five class of regional development were identified. Class 1 included cities with the highest level of regional development. Class 2 is represented by cities with relatively high, but not the highest level of development. Class 3 includes cities with a moderate level of development. Class 4 includes cities with a low level of development, in need of development support or intervention, while the final class five includes cities with the lowest level of regional development.

The survey made it possible not only to assess the relative level of development of cities, but also to identify areas requiring support in the context of spatial planning and regional policy.

4. Results

The first step in the creation of a ranking of selected European cities in terms of regional development was the estimation of correlations between diagnostic variables, which is presented below (Table 1).

Table 1.
Set of variables characterizing the potential for implementing new technologies and artificial intelligence as a response to the challenges facing selected cities

Symbol*	Diagnostic variables
$X_{1(s)}$	population living in private households (excluding institutional households)
$X_{2(s)}$	lone pensioner (above retirement age) households
$X_{3(s)}$	number of registered cars per 1000 population
$X_{4(s)}$	economically active population, total
$X_{5(s)}$	total employment/jobs (work place based)
$X_{6(s)}$	employment (jobs) in mining, manufacturing, energy (nace rev. 2, b-e)
$X_{7(s)}$	employment (jobs) in trade, transport, hotels, restaurants (nace rev. 2, g to i)
$X_{8(s)}$	employment (jobs) in information and communication (nace rev. 2, j)
$X_{9(s)}$	employment (jobs) in financial and insurance activities (nace rev. 2, k)
$X_{10(s)}$	employment (jobs) in professional, scientific and technical activities; administrative and support service activities (nace rev. 2, m and n)

* (s) – stimulant, (d) – destimulant.

Source: own elaboration.

The starting point for further research was the matrix of coefficients of correlation between potential diagnostic features (Table 2).

Table 2.
Matrix of correlation between analyzed diagnostics variables

	X1	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*
X1	1.00	0.98	0.08	1.00	0.99	0.95	0.98	0.98	0.97	0.97
X2	0.98	1.00	0.16	0.97	0.94	0.92	0.93	0.93	0.96	0.91
X3	0.08	0.16	1.00	0.04	-0.03	-0.08	0.07	-0.04	-0.06	0.06
X4	1.00	0.97	0.04	1.00	0.99	0.96	0.99	0.99	0.97	0.98
X5	0.99	0.94	-0.03	0.99	1.00	0.97	0.99	0.99	0.96	0.98
X6	0.95	0.92	-0.08	0.96	0.97	1.00	0.95	0.96	0.94	0.93
X7	0.98	0.93	0.07	0.99	0.99	0.95	1.00	0.99	0.92	0.99
X8	0.98	0.93	-0.04	0.99	0.99	0.96	0.99	1.00	0.94	0.99
X9	0.97	0.96	-0.06	0.97	0.96	0.94	0.92	0.94	1.00	0.90
X10	0.97	0.91	0.06	0.98	0.98	0.93	0.99	0.99	0.90	1.00

Source: author's calculations.

Using the next criterion for the selection of diagnostic variables, namely a sufficiently high degree of variability, no reduction in diagnostic variables was made (Table 3). For no diagnostic variable did the estimated coefficient of variation take values below 10%. The variation in the adopted characteristics indicates high significance between variables.

Table 3.
Numerical characteristics of diagnostic features in selected cities

Characteristic	**Diagnostic variables**									
	$X_{1(s)}$	**$X_{2(s)}$**	**$X_{3(s)}$**	**$X_{4(s)}$**	**$X_{5(s)}$**	**$X_{6(s)}$**	**$X_{7(s)}$**	**$X_{8(s)}$**	**$X_{9(s)}$**	**$X_{10(s)}$**
Maximum	12936,8	687,0	0,6	6710,6	6165,9	444,7	1395,9	433,3	354,3	1047,3
Arithmetic mean	3786,1	209,4	452,54	1960,8	1858,9	153,3	473,7	131,7	81,3	337,4
Standard deviation	3764,3	190,8	0,08	1948,9	1805,2	124,1	419,5	130,8	101,2	335,9
Coefficient of variation (%)	99,42	91,12	19,13	99,40	97,11	80,97	88,57	99,28	124,51	99,59

Source: author's calculations.

Based on an examination of the coefficient of variation and linear correlation coefficient, four diagnostic variables were selected (Table 4).

Table 4.
Set of diagnostic variables selected for creation of ranking

Symbol*	Diagnostic variables
$X_{1(s)}$	population living in private households (excluding institutional households)
$X_{2(s)}$	lone pensioner (above retirement age) households
$X_{4(s)}$	economically active population, total
$X_{5(s)}$	total employment/jobs (work place based)
$X_{6(s)}$	employment (jobs) in mining, manufacturing, energy (nace rev. 2, b-e)
$X_{7(s)}$	employment (jobs) in trade, transport, hotels, restaurants (nace rev. 2, g to i)
$X_{8(s)}$	employment (jobs) in information and communication (nace rev. 2, j)
$X_{9(s)}$	employment (jobs) in financial and insurance activities (nace rev. 2, k)
$X_{10(s)}$	employment (jobs) in professional, scientific and technical activities; administrative and support service activities (nace rev. 2, m and n)

* (s) – stimulant.

Source: own elaboration.

Using a taxonomic method, a ranking of the nine European cities selected for the study was created, reflecting the potential for the development of artificial intelligence and new technologies, as a response to the challenges facing the selected urban centers (Table 5).

Table 5.
Ranking of European cities according to the standardized sum index

Class	City
1	Paris
2	Madrid
3	Roma, Budapest, Brussel
4	Helsinki, Riga, Vilnius
5	Tallin

Source: own elaboration.

The final distribution of cities was influenced by the nine diagnostic variables indicated in Table 4. The variables illustrate the scale of the phenomenon of the possibility of implementing solutions using artificial intelligence as part of smart city and sustainable development strategies, referring to the number of residents, their level of education, wealth, or loneliness.

5. Discussion and Conclusions

Smart cities aim to effectively manage the progressive process of urbanization, energy consumption, care for the environment, appreciate the financial and living standards of residents, and increase the capacity of human capital to effectively use and implement modern information and communication technologies (ICT). Multisectoral cooperation plays an important role in the smart city project, starting with smart transportation, cyber security, smart grids (SG), and next-generation communications supported by UAVs (5G and B5G) (Ullah et al., 2020). All of the previous smart city sectors are heavily influenced by big data analytics and the effective use of artificial intelligence, machine learning and DRL-based techniques that can increase their efficiency and scalability in a smart city project.

Nowadays, it is often indicated in the literature that waste management is one of the biggest challenges facing the world, whether in developed or developing countries. Population growth has led to a significant deterioration in the hygienic situation of the waste management system (Venkatesh et al., 2022). Many solutions are being implemented in the smart city to support waste management.

Smart infrastructure, an essential component of smart cities, is equipped with wireless sensor networks that autonomously collect, analyze and transmit structural data, called "smart monitoring" (Luckey et al., 2021). The goals of intelligent monitoring, indicated in the literature, can also respond to sustainable development goals. Artificial intelligence-based applications targeting smart city residents have been adopted by various developing and developed countries around the world. Artificial intelligence is and will be an indispensable part of the smart city (Ashwini, 2022). In addition, urban mobility has seen significant innovations through artificial intelligence applications such as autonomous vehicles (AVs), electric vehicles (EVs) and unmanned aerial vehicles (UAVs). The impact of artificial intelligence can be seen in the areas of energy management and sustainable development practices, health care, environmental management, or the industrial sector (Szpilko, 2023).

The conducted study of the literature on the subject and the analysis of statistical data using the taxonomic method made it possible to verify the research hypothesis and formulate theoretical, methodological and pragmatic conclusions. A positive verification of the research hypothesis was made, indicating that artificial intelligence and new technologies level social problems in smart cities. As part of the methodological conclusions, it should be pointed out that the taxonomic methods used, made it possible to categorize the cities selected for the study in terms of the development potential of the smart city and to indicate the similarities of the ongoing changes in the analyzed metropolises. The main conclusion of a theoretical nature is that the topic of smart city considerations in combination with sustainable development and artificial intelligence has become a permanent part of economic science. Referring to the pragmatic insights of the research, first of all, there is a noticeable increase in the importance of artificial intelligence as a tool to support the implementation of smart city strategies. Secondly, the implementation of AI in urban policy is a multi-factor process. It depends not only on the level of digital sophistication, the availability of data, the competence of officials, the infrastructure and organizational culture of the administration, cooperation with the private sector and academia, but also and perhaps most importantly on the residents. Thirdly, smart city development strategies are a kind of response to the realization of sustainable development goals. The suggestion for local authorities with custody of smart city development is to focus even more on the needs of local residents in terms of education about sustainable lifestyles and the use of artificial intelligence.

References

1. Anttiroiko, A.V., Sahamies, K. (2022, June). *Designing city service ecosystems: the case of the city of Espoo in the capital region of Finland.* International Conference on Human-Computer Interaction. Cham: Springer International Publishing, pp. 139-157.
2. Arduin, P., Negre, E., Rosenthal-Sabroux, C. (2016). *Knowledge and decision for smart cities initiatives: cases of Paris and Nice.* 2016 International Conference on Industrial Informatics and Computer Systems (CIICS). https://doi.org/10.1109/iccsii.2016.7462421
3. Ashwini, B.P., Savithramma, R.M. (2022). *Artificial Intelligence in Smart city applications: An overview.* 2022 6th international conference on intelligent computing and control systems (ICICCS). IEEE, pp. 986-993.
4. Blicharz, J. (2023). *Inteligentne miasta i sztuczna inteligencja*. Wrocław: Wydawnictwo Uniwersytetu Wrocławskiego.
5. Chudy-Hyski, D. (2006). Ocena wybranych uwarunkowań rozwoju funkcji turystycznej obszaru [The evaluation of chosen conditions of development of tourism function of an area]. *Infrastruktura i ekologia obszarów wiejskich, No. 1.* Polska Akademia Nauk [Polish Academy of Sciences].
6. Czemiel-Grzybowska, W. (2023). Trendy rozwoju zrównoważonej przedsiębiorczości technologicznej opartej na sztucznej inteligencji. *Akademia Zarządzania*, *7(4).*
7. Czyżewska-Misztal, D. (2024). Wykorzystanie sztucznej inteligencji na rzecz rozwoju miast i regionów. In: *Droga do zrównoważonej gospodarki światowej* (pp. 43-52). Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu.
8. Hamadneh, J., Jaber, A. (2023). Modeling of intra-city transport choice behaviour in Budapest, Hungary. *Journal of Urban Mobility, 3, 100049*. https://doi.org/10.1016/j.urbmob.2023.100049
9. Lee, S., Lee, D. (2015). A study on analysis & outlook of smart city based on actual cases. *International Journal of Smart Home, 9(7),* 181-188. https://doi.org/10.14257/ijsh.2015.9.7.18
10. Legutko-Kobus, P. (2021). E-partycypacja i Iso 37120 jako wyznacznik implementacji rozwoju zrównoważonego w Smart City. *Studia Ecologiae Et Bioethicae, 19(1),* 71-82. https://doi.org/10.21697/seb.2021.19.1.06
11. Ljepava, N. (2022). Ai-enabled marketing solutions in marketing decision making: AI application in different stages of marketing process. *TEM Journal*, 1308-1315. https://doi.org/10.18421/tem113-40
12. Luckey, D., Fritz, H., Legatiuk, D., Dragos, K., Smarsly, K. (2021). *Artificial intelligence techniques for smart city applications.* Proceedings of the 18th International Conference on Computing in Civil and Building Engineering: ICCCBE 2020. Springer International Publishing, pp. 3-15.

13. Mierzejewska, L. (2015). Zrównoważony rozwój miasta – wybrane sposoby pojmowania, koncepcje, modele. *Problemy Rozwoju Miast, vol. 12, no. 3*.
14. Murawska, A. (2010). Klasyfikacja województw pod względem rozwoju gospodarczego za pomocą metod taksonomicznych [Classification of provinces in terms of economic development by means of taxonomic methods]. *Polskie Stowarzyszenie Zarządzania Wiedzą, Seria: Studia i Materiały, No. 33*.
15. Niedziela-Wawrzyniak, S. (2023). Zielone ściany w środowiskach miejskich: katalizatory innowacji i zdolności adaptacyjnych miast. *Zeszyty Naukowe Wyższej Szkoły Technicznej W Katowicach, 17,* 21-42. https://doi.org/10.54264/0073.
16. Orejon-Sanchez, R.D., Crespo-Garcia, D., Andres-Diaz, J.R., Gago-Calderon, A. (2022). Rozwój inteligentnych miast w Hiszpanii: porównanie wskaźników technicznych i społecznych w odniesieniu do miast europejskich. *Zrównoważone miasta i społeczeństwo*, *81*, 103828.
17. Podgórniak-Krzykacz, A., Przywojska, J. (2023). Skoncentrowana na ludziach transformacja miast w kierunku inteligentnego zrównoważonego rozwoju. *Władza Sądzenia, 25,* 70-87. https://doi.org/10.18778/2300-1690.25.05
18. Raszyd, K.I., Wesołowska, A., Tomaszewska, K. (2024). Sztuczna Inteligencja w nauce– jak studenci wykorzystują AI w edukacji wyższej. *Akademia Zarządzania*, *8*(3).
19. Szarek, J. (2021). *High-Tech Sector in The Benelux Countries Compared to The Remainder of The European Union – A Taxonomic Analysis*. Proceedings of the 38th International Business Information Management Association Conference (IBIMA): Digital healthcare solutions for remote care delivery and better patient outcomes. K.S. Soliman (ed.), Proceedings of the ... International Business Information Management Association Conference, 2021, International Business Information Management Association, pp. 4264-4271, ISBN 978-0-9998551-7-1
20. Szarek-Orlecka, J. (2025). *Taxonomic measurement of regional diversification of the level of innovation in Poland.* Proceedings of the 45th International Business Information Management Association Conference (IBIMA): Business, Marketing, Management, and Human Resources Conference. K.S. Soliman (ed.), Proceedings of the ... International Business Information Management Association Conference, 2025, International Business Information Management Association, ISBN: 979-8-9867719-6-0
21. Szews, P. (2024). Sztuczna inteligencja w digital marketingu. *Media i Społeczeństwo*, *20*(1).
22. Szpilko, D., Naharro, F.J., Lăzăroiu, G., Nica, E., de la Torre Gallegos, A. (2023). *Artificial intelligence in the smart city—a literature review*.
23. Ullah, Z., Al-Turjman, F., Mostarda, L., Gagliardi, R. (2020). Applications of artificial intelligence and machine learning in smart cities. *Computer Communications, 154*, 313-323.

24. Venkatesh, A.N., Naved, M., Fakih, A.H., Kshirsagar, P.R., Vijayakumar, P. (2022). An approach for smart city applications using artificial intelligence. *AIP Conference Proceedings, Vol. 2393, No. 1.* AIP Publishing.
25. Widuch, A. (2022). Koncepcje Smart City w wybranych miastach Zagłębia Ruhry. *Academic Review of Business and Economics, 2,* 37-52. https://doi.org/10.22367/arbe.2022.02.03