

# ARTIFICIAL INTELLIGENCE IN LEARNING AND WORK PRACTICES: URBAN–RURAL DIFFERENCES IN PERCEIVED PRODUCTIVITY AND COMPETITIVENESS

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## ABSTRACT

**Aim:** Artificial intelligence (AI) is increasingly shaping learning processes and work practices, with important implications for productivity and regional competitiveness. However, the benefits of AI adoption may not be evenly distributed across urban and rural contexts. This study examines how individuals living in large cities, small cities, and rural areas perceive and use AI in learning and professional activities, and how they evaluate its economic benefits and associated risks. **Method:** The study is based on an online survey conducted in 2025 in Lithuania, comprising 17 Likert-scale items measuring perceived productivity benefits, learning support, digital skills, the future relevance of AI, and perceived risks. The final sample comprised 120 valid and fully completed responses ( $N = 120$ ). Descriptive statistics were used to summarize response patterns, and pairwise Welch's t-tests were applied to explore differences across residential contexts. **Results:** The results indicate generally positive attitudes toward AI across all groups, particularly regarding overall time-saving, improved decision-making, and enhanced competitiveness. Statistically significant differences were observed only between respondents living in large cities and small cities, with greater concern about potential job displacement. **Conclusions:** Overall, the findings of the sample suggest that while AI is widely perceived as a generally productivity-enhancing tool across regions, place-based disparities in skills and perceptions persist, underscoring the need for targeted training, institutional support, and inclusive digital policies to strengthen balanced regional competitiveness.

**Key words:** artificial intelligence, labor market, urban–rural differences, digital skills, regional development

**JEL codes:** O33, R11, J24

## INTRODUCTION

Artificial intelligence (AI) is increasingly recognized as a key driver of economic transformation, with significant implications for productivity growth, labor markets, and competitiveness across regions. At the macroeconomic level, AI adoption contributes to productivity gains by automating routine activities, improving data processing and analysis, and sup-

porting more informed and timely decision-making, thereby influencing economic growth and income distribution (Filippucci et al., 2024). Recent research further emphasizes that AI can act as a catalyst for rural economic development by enabling technological upgrading in traditionally lagging sectors such as agriculture, public services, and local administration (Zhu, 2025). These effects are particularly relevant in knowledge-intensive sectors, where AI can enhance

efficiency, reduce operational costs, and partially offset skill shortages. However, the economic benefits of AI are not distributed evenly, raising concerns about spatial inequalities between urban and rural areas.

From a regional development perspective, urban–rural disparities remain a central issue in AI adoption. Research focusing on rural and small-town contexts shows that while enterprises and workers in these areas increasingly recognize the potential economic value of AI, adoption is often constrained by weaker digital infrastructure, limited access to advanced technologies, and shortages of specialized skills (Dowell et al., 2024). Studies on rural AI diffusion indicate that without targeted policy support and infrastructure investment, AI adoption may reinforce rather than reduce existing regional inequalities (Zhu, 2025). As a result, rural economies may face a relative disadvantage in capturing productivity gains from AI compared with large urban centers, where digital ecosystems, innovation networks, and human capital are more developed (Bijalwan et al., 2024). These disparities highlight the importance of understanding AI not only as a technological innovation but also as a factor shaping regional competitiveness.

Education and human capital development play a crucial role in mediating the economic impact of AI across regions. AI-related skills are becoming essential for employability and labor-market resilience, particularly as automation reshapes job tasks and occupational structures. Empirical evidence suggests that AI development can improve the quality of rural employment by expanding access to learning and training opportunities, thereby enhancing workers' job competitiveness, although these effects vary across regions (Li et al., 2025). However, access to AI education and training remains uneven. López Costa (2025) demonstrates that rural schools and training institutions face structural challenges in integrating AI and data literacy into curricula, potentially reinforcing existing skill gaps between urban and rural populations. From an economic standpoint, such gaps may limit the capacity of rural labor markets to adapt to technological change and benefit from AI-driven productivity improvements.

Higher education institutions and training providers are therefore increasingly viewed as key actors in re-

gional economic development. Studies in accounting and management education indicate that meaningful AI integration depends on institutional readiness, curriculum design, and alignment with labor-market needs rather than formal program labels alone (O'Hara et al., 2024). From a managerial and organizational perspective, leadership, policy clarity, and investment in digital infrastructure are critical enablers of effective AI adoption in educational settings (Huma et al., 2025; Shahzad et al., 2025). Where such conditions are absent, AI learning tends to occur informally and unevenly, potentially amplifying urban–rural disparities in digital competence and economic opportunity.

Empirical evidence on student and early-career professional engagement with AI further illustrates these dynamics. Research shows that students widely use AI tools for general learning support, text generation, and data processing, and strongly associate AI with efficiency gains, automation of routine tasks, and improved accuracy – attributes directly linked to productivity enhancement. At the same time, concerns about over-reliance, data security, and the erosion of critical thinking remain salient, reflecting an awareness of the economic and professional risks associated with uncritical AI adoption (Vieriu & Petrea, 2025). Importantly, studies grounded in technology adoption frameworks suggest that perceived usefulness alone is insufficient to ensure effective AI uptake; ease of use, access to training, and opportunities for practical application are equally important determinants (Gaviria Rodríguez et al., 2025).

The literature also reveals a persistent gap between general-purpose AI use and professionally embedded applications that directly influence economic performance. While AI is widely used for generic tasks, its adoption in specialized domains remains limited (Kokina et al., 2025). Evidence from agricultural and rural labor markets indicates that AI can simultaneously displace low- and medium-skilled jobs while creating new opportunities for high-skilled labor, underscoring the importance of skills development and adaptive learning systems (Yang et al., 2025). These challenges may be particularly pronounced in rural and small-town organizations, which often operate with limited resources and lower capacity for technological experimentation.

Taken together, the existing literature highlights both the economic potential of AI to enhance productivity and competitiveness and the structural constraints that shape its uneven diffusion across urban and rural contexts. Recent empirical studies show that AI can support rural industrial revitalization and structural upgrading, particularly in technologically lagging regions, but that outcomes vary significantly across local contexts (Zhao & Yang, 2025). While prior research has examined AI adoption at organizational, sectoral, or educational levels, fewer studies have focused on how individuals in different residential settings perceive and use AI in their everyday learning and work practices. Addressing this gap is critical for understanding whether AI can contribute to more balanced regional development or whether it risks reinforcing existing urban–rural economic disparities. By analyzing AI use, perceived benefits, and learning needs across large cities, small cities, and rural areas, the present study contributes empirical evidence relevant to discussions on inclusive digital transformation and regional economic competitiveness.

Building on the reviewed literature and the identified research gap, this study addresses the following research questions:

- RQ1: How do individuals living in large cities, small cities, and rural areas use artificial intelligence in their learning and work practices, and how do they perceive its effects on productivity and competitiveness?
- RQ2: Are there significant differences between large-city, small-city, and rural residents in their perceptions of AI-related digital skills, learning support, and associated risks?

Answering RQ1, we expect generally positive use and perceptions of AI for learning and working across large cities, small cities, and rural areas, especially regarding time saving, learning support, and competitiveness, with slightly higher perceived benefits and digital skills among large-city residents. Answering RQ2, we expect limited differences between residential groups, with similar assessments of AI-related learning support and risks, but stronger concerns about future job demand among large-city respondents.

## AIM AND METHOD

The study employed a quantitative survey design to examine perceptions and use of artificial intelligence (AI) in learning and work contexts across different places of residence. Data were collected in 2025 using a self-administered online questionnaire distributed via institutional networks and social media to respondents living in large cities, small cities, and rural areas in Lithuania. A total of 470 questionnaires were distributed, of which 120 were returned as valid and fully completed, resulting in a final sample size of  $N = 120$ . The final sample comprised respondents from large cities ( $n = 80$ ; 66.7%), small cities ( $n = 28$ ; 23.3%), and rural areas ( $n = 12$ ; 10.0%).

The survey instrument comprised 17 Likert-scale statements (E1–E17) measuring attitudes toward AI-related productivity benefits, learning support, digital skills, perceived risks, and future relevance. Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire also included background variables capturing demographic and socioeconomic characteristics, such as gender, education, employment status, income level, and place of residence.

Data from three identical survey versions were merged and harmonized prior to analysis. Descriptive statistics were used to summarize overall response patterns. Mean values and standard deviations were calculated for each survey item by place of residence, and descriptive statistics were used to summarize overall response patterns. To explore differences between groups, pairwise Welch's *t*-tests were conducted, which are appropriate for unequal sample sizes and variances. Although Likert-scale responses are ordinal, parametric tests were applied because the data approximate interval-level measurement and the sample size is sufficient; this approach is commonly accepted in similar studies. Given the exploratory nature of the study and the relatively small rural subsample, the analysis focused on identifying indicative patterns rather than making causal claims; accordingly, *p*-values were not adjusted for multiple comparisons.

## RESULTS

The final sample comprised respondents residing predominantly in large cities (66.7%), followed by small cities (23.3%) and rural areas (10.0%). Respondents were in a broadly similar age group across locations, with a mean age of approximately 28.7 years in large cities, 29.4 in small cities, and 30.2 in rural areas, indicating no substantial age differences between groups. In terms of gender, the sample was moderately imbalanced, with women representing a clear majority (around 60–65%), while men accounted for roughly one third of respondents, and a small proportion preferred not to disclose their gender. Most respondents had higher education, with over half holding a bachelor's degree and a substantial share reporting master's-level or equivalent education, while a smaller proportion had vocational or secondary education. Most participants were employed or combined work with studies, indicating strong integration into the labor market. Income levels were distributed across low, medium, and higher brackets, with middle-income respondents forming the largest group, while lower- and higher-income categories were each represented by smaller but meaningful shares. Overall, the sample reflects a relatively well-educated, economically active population with diverse socioeconomic backgrounds, suitable for exploratory analysis of AI-related attitudes across different places of residence.

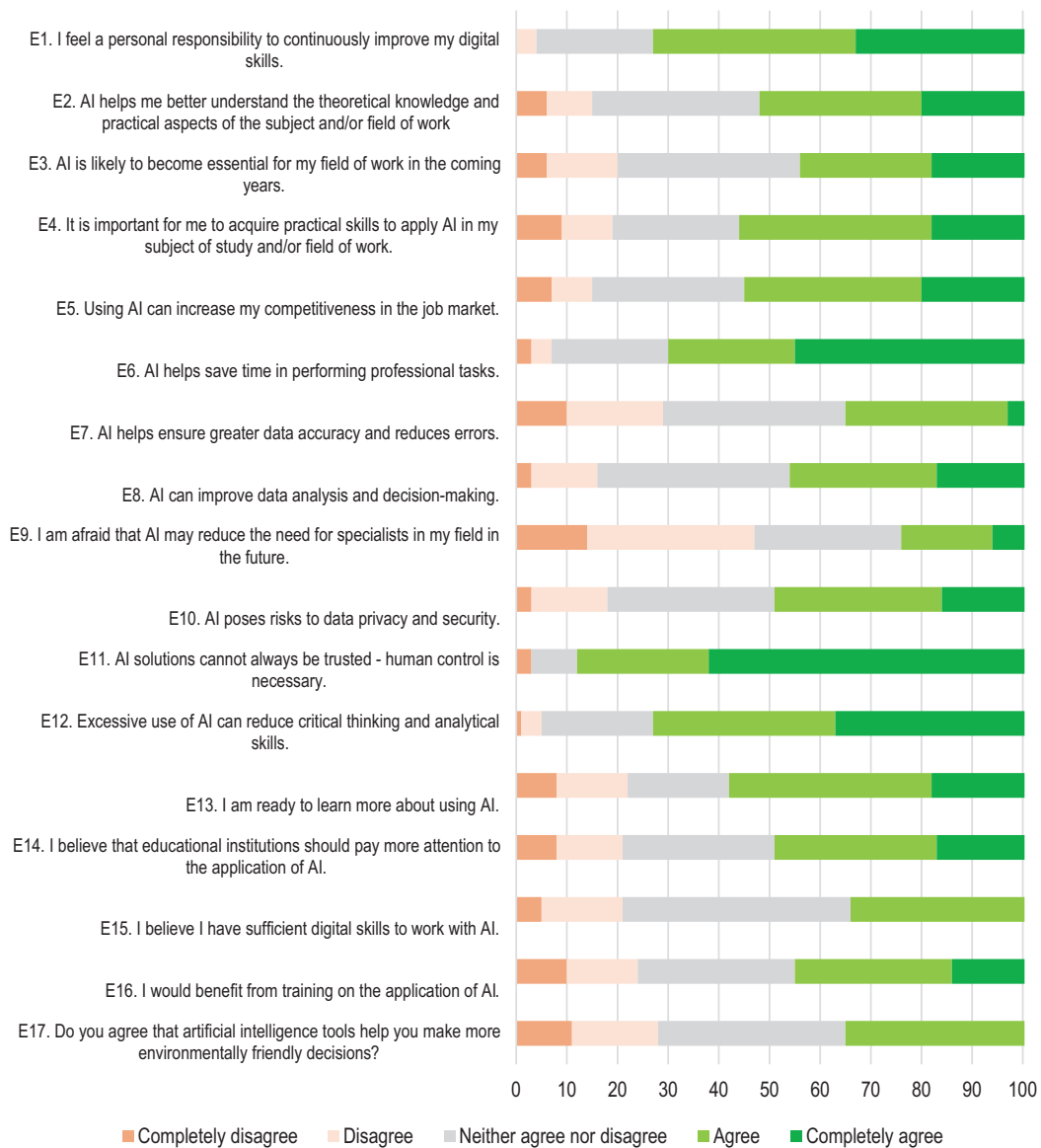
The results also suggest that the sample consists largely of digitally literate individuals across all residential groups, as reflected in similar levels of self-assessed digital skills (3.48, 3.21, 3.08 on a 1–5 scale for large cities, small cities, and rural areas, respectively) and a consistently high sense of responsibility to improve them (4.25, 3.93, 4.33). Second, the results also suggest a degree of convergence in access to and use of AI tools, as indicated by comparable frequencies of general AI use (4.12, 3.86, 3.65) and learning-related use (3.61, 3.69, 3.41) across all groups.

Overall, the distribution of responses indicates a generally positive, pragmatic attitude toward artificial intelligence across all survey items (Fig. 1). Strong agreement is most evident for statements related to personal digital responsibility (E1), time-saving benefits of AI (E6), the necessity of human control

over AI solutions (E11), and concerns about the potential impact of excessive AI use on critical thinking (E12), indicating both high engagement and reflective caution. Respondents largely agree that AI can enhance competitiveness, improve data analysis and decision-making, increase accuracy, and support learning and professional tasks (E5–E8), although these items also show a notable share of neutral responses, suggesting varying levels of experience or confidence. Perceptions of future relevance and the need for practical AI skills and institutional support (E3, E4, E14, E16) are predominantly positive, highlighting expectations that AI will play an increasingly important role in education and work. At the same time, attitudes toward risks, such as job displacement, privacy, and security concerns (E9, E10), are more mixed, reflecting ambivalence rather than outright opposition. Finally, readiness to continue learning about AI (E13) is high, while confidence in having sufficient digital skills (E15) is more moderate, underscoring the ongoing need for targeted training and support to ensure effective and responsible AI adoption.

The comparison across large cities, small cities, and rural areas reveals broadly similar and generally positive attitudes toward artificial intelligence, with only modest variations between groups (Figs. 2 and 3). As shown in Figure 2, respondents in all three settings reported strong agreement regarding personal responsibility for improving digital skills, the usefulness of AI for saving time, improving data analysis and decision-making, and its growing importance for their field of work. Residents of large cities tended to report slightly higher confidence in their digital skills and somewhat stronger perceptions of AI's analytical and professional benefits, while respondents from rural areas often expressed comparable or even slightly higher readiness to learn more about AI and to acquire practical application skills.

At the same time, as illustrated in Figure 3, attitudes toward potential risks – including job displacement, data privacy concerns, and the need for human oversight – were more moderate and mixed across all groups, with no pronounced divergence by place of residence. Across locations, there was a consistent recognition that AI systems require human control and that excessive reliance on AI may negatively

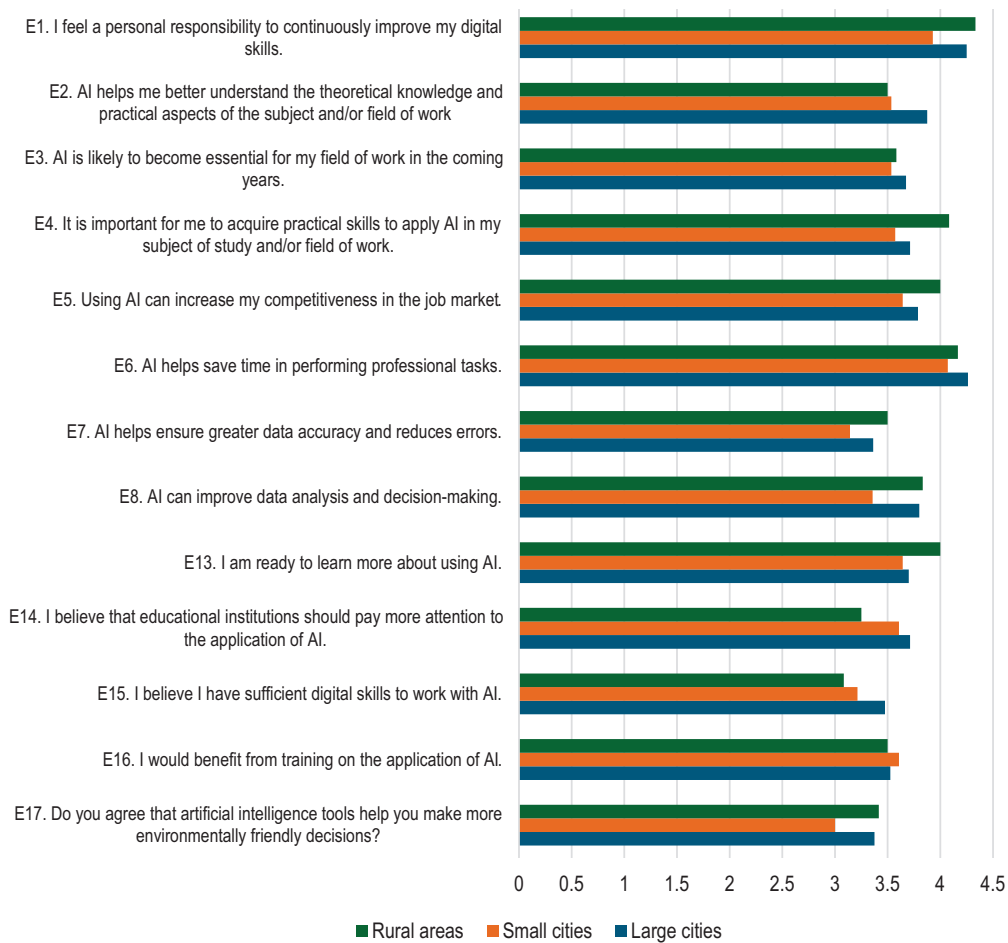


**Fig. 1.** Five-point scale responses to AI-related attitude statements [%]

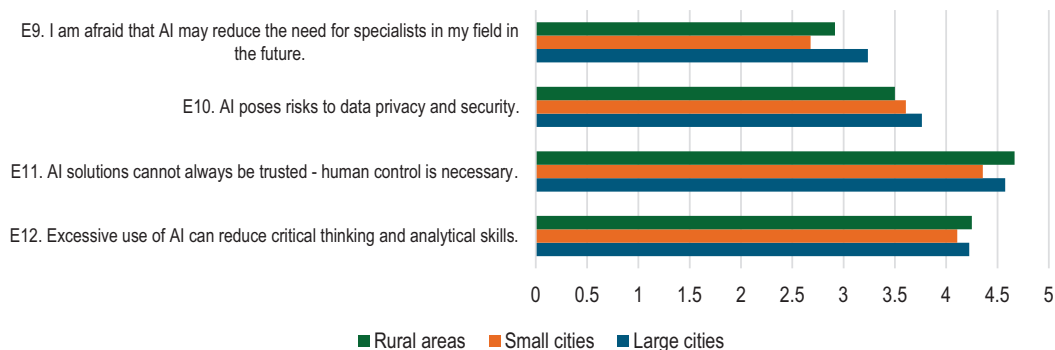
Source: authors' calculations.

affect critical thinking, indicating a shared awareness of both benefits and risks. Overall, the results suggest that AI is perceived as increasingly relevant and valuable across urban, small-city, and rural contexts alike, while also highlighting a common need for continued training, institutional support, and responsible implementation regardless of geographic location.

Pairwise Welch's t-tests revealed a statistically significant difference only between large-city and small-city respondents with respect to concerns that artificial intelligence may reduce the future need for specialists in their field (E9;  $t = 2.07$ ,  $p = 0.043$ , Cohen's  $d = 0.44$ ), with large-city respondents expressing higher levels of concern. No statistically significant



**Fig. 2.** Mean responses to AI-related benefits and learning aspects by place of residence (large cities, small cities, and rural areas)  
Source: authors' calculations.



**Fig. 3.** Mean responses to AI-related risks and concerns by place of residence (large cities, small cities, and rural areas)  
Source: authors' calculations.

differences were detected between large-city and small-city respondents in perceived analytical benefits of AI (E8;  $t = 1.66$ ,  $p = 0.106$ ) or self-assessed digital skills (E15;  $t = 1.20$ ,  $p = 0.234$ ). Furthermore, no statistically significant differences were detected between urban and rural respondents or between small-city and rural respondents across any of the examined items (all  $p > 0.05$ ). It should be noted that the rural subsample is relatively small ( $n = 12$ ), which limits statistical power and reduces the likelihood of detecting statistically significant differences involving this group.

## DISCUSSION

The findings of this study reinforce existing evidence that artificial intelligence is increasingly perceived as a valuable tool for enhancing productivity, learning efficiency, and decision-making, while also revealing important spatial nuances in these perceptions. Overall positive attitudes toward AI's time-saving and analytical benefits align with macro-level evidence that AI contributes to productivity growth and efficiency gains across sectors (Filippucci et al., 2024). Respondents' strong support for AI-assisted decision-making and competitiveness suggests that AI is increasingly viewed as an economic resource rather than merely a technological novelty.

At the same time, the results highlight subtle yet meaningful differences between respondents living in large cities and those in small cities. Urban respondents reported higher confidence in their digital skills and stronger agreement with AI's analytical benefits, consistent with prior research showing that urban environments tend to offer greater access to digital infrastructure, training opportunities, and innovation ecosystems (Dowell et al., 2024). These findings suggest that spatial context continues to shape the capacity to fully leverage AI, even when overall attitudes are broadly positive.

Concerns related to job displacement, data security, and over-reliance on AI were evident across all residential contexts, supporting earlier work that emphasizes the need for human oversight, ethical safeguards, and critical engagement with AI technologies (Vieriu & Petrea, 2025). Importantly, these concerns did not negate respondents' willingness to adopt AI, indicating

a balanced perspective that recognizes both economic benefits and risks. This pattern is consistent with studies showing that perceived usefulness must be complemented by trust, usability, and institutional support to sustain meaningful adoption (Gaviria Rodríguez et al., 2025).

Finally, the relatively similar perceptions observed between small-city and rural respondents may reflect shared structural conditions, such as limited access to formal AI training and fewer organizational resources, as highlighted in prior research on rural education and enterprise contexts (Dowell et al., 2024; López Costa, 2025). From a policy and regional development perspective, these findings underscore the importance of targeted investments in digital infrastructure, AI-related skills development, and institutional support mechanisms to ensure that AI contributes to balanced regional competitiveness rather than reinforcing existing urban–rural disparities.

## CONCLUSIONS

This study analyzed the use of artificial intelligence in learning and work practices and examined differences in perceived productivity, competitiveness, skills, and risks across large-city, small-city, and rural contexts. The results indicate generally positive attitudes toward AI in all residential groups, particularly regarding its potential to support learning, save time, and improve data accuracy. Empirical evidence shows that differences between residential groups are limited, with a statistically significant difference identified only between large-city and small-city respondents in concerns about the future demand for specialists.

The absence of significant differences between urban and rural respondents across most dimensions suggests a relatively homogeneous diffusion of general-purpose AI tools and perceptions, regardless of place of residence. These findings imply that policies and educational initiatives aimed at enhancing AI-related skills should address learners and workers across all regions rather than focusing exclusively on urban or rural areas.

Several limitations should be acknowledged. The study relies on self-reported perceptions rather than objective measures of productivity, and the rural subsample is relatively small, which may

limit statistical power. As participation was voluntary and self-selected, the sample may be biased toward more digitally engaged individuals; accordingly, the findings should be interpreted as exploratory and not fully representative of the broader population. In addition, the cross-sectional design does not allow for causal interpretation or analysis of changes over time. Future research could build on these findings by using longitudinal data, larger and more balanced samples, and by examining sector-specific applications of AI to better understand its impact on productivity and competitiveness across regions.

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## **SZTUCZNA INTELIGENCJA W PROCESACH UCZENIA SIĘ I PRAKTYKACH PRACY: RÓŻNICE MIEJSKO-WIEJSKIE W POSTRZEGANEJ PRODUKTYWNOŚCI I KONKURENCYJNOŚCI**

### **STRESZCZENIE**

**Cel:** Sztuczna inteligencja (AI) w coraz większym stopniu kształtuje procesy uczenia się oraz praktyki zawodowe, wywierając istotny wpływ na produktywność i konkurencyjność regionalną. Korzyści wynikające z wdrażania AI mogą jednak nie być równomiernie rozłożone pomiędzy obszary miejskie i wiejskie. Celem badania było wskazanie, jak mieszkańcy dużych miast, małych miast oraz obszarów wiejskich postrzegają i wykorzystują AI w procesach uczenia się oraz działalności zawodowej, a także jak oceniają jej korzyści ekonomiczne i związane z nią ryzyko. **Metoda:** Badanie przeprowadzono w 2025 roku na Litwie z użyciem kwestionariusza ankiety online, obejmującego 17 pozycji w skali Likerta, mierzących postrzegane korzyści produktywnościowe, wsparcie procesu uczenia się, kompetencje cyfrowe, przyszłe znaczenie AI oraz postrzegane ryzyko. Ostateczna próba badawcza obejmowała 120 poprawnie i kompletnie wypełnionych kwestionariuszy ( $N = 120$ ). Do podsumowania wzorców odpowiedzi zastosowano statystyki opisowe, do analizy różnic pomiędzy typami miejsca zamieszkania wykorzystano zaś test  $t$  Welcha dla prób niezależnych. **Wyniki:** Wykazano empirycznie pozytywne postawy wobec AI we wszystkich badanych grupach, szczególnie w odniesieniu do oszczędności czasu, poprawy jakości podejmowania decyzji oraz wzrostu konkurencyjności. Statystycznie istotne różnice zaobserwowano jedynie pomiędzy respondentami zamieszkującymi duże miasta i małe miasta, przy czym mieszkańcy dużych miast wykazywali większe obawy dotyczące potencjalnego wypierania pracowników przez AI. **Wnioski:** Uzyskane wyniki w badanej próbie sugerują, że AI jest postrzegana jako narzędzie zwiększające produktywność niezależnie od regionu, jednak nadal występują przestrzennie zróżnicowane dysproporcje w zakresie kompetencji i percepcji. Podkreśla to potrzebę wdrażania ukierunkowanych szkoleń, wsparcia instytucjonalnego oraz inkluzywnych polityk cyfrowych sprzyjających wzmocnieniu zrównoważonej konkurencyjności regionalnej.

**Słowa kluczowe:** sztuczna inteligencja, rynek pracy, różnice miejsko-wiejskie, kompetencje cyfrowe, rozwój regionalny