Addressing Digital and AI Skills Gaps in European Living Areas: A Comparative Analysis of Small and Large Communities

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Abstract

As Artificial Intelligence (AI) continues to permeate various aspects of societies, understanding the disparities in AI knowledge and skills across different living areas becomes imperative. Small living areas have emerged as significant contributors to Europe's economy, offering an alternative to the bustling environment of larger cities for those seeking an improved quality of life. Nonetheless, they often encounter challenges related to digital infrastructure, access to financial resources, and digital skills gaps, limiting their economic and social growth prospects. This study investigates the digital and AI skills gaps in the context of small and large European living areas, shedding light on the potential hindrances to unleashing the full economic and social potentials of these regions in an AI-enabled economy. Drawing from a comprehensive dataset encompassing 4,006 respondents across eight EU countries, this research examines the current perceptions and understandings of AI and digital skills within two distinct population groups: residents of smaller living areas and their counterparts in larger communities. Through bivariate analysis, notable insights are revealed concerning trust in AI solutions and entities, self-assessed digital skills, AI Awareness, AI Attitudes and demography variables in both population groups. These insights may refer to the significance of addressing digital and AI skills gaps in fostering growth and preparedness for the AI-driven future. As AI becomes increasingly integral to various aspects of society, targeted interventions and policies are essential to bridge these gaps and enable individuals and communities to harness the transformative potential of AI-enabled economies.

Introduction

Artificial Intelligence (AI) has not only gathered considerable attention in technologies but has also begun to infuse the daily lives of ordinary people. As AI applications increasingly find their way into various facets of society such as smart cities (Pham, Mai, and Massey 2016), education (Mai, Crane, and Bezbradica 2019, 2023) and finance (Nguyen et al. 2022, 2023), the acquisition and utilisation of AI skills have emerged as critical factors in ensuring the safe and effective use of these technologies. This paradigm shift towards AI-driven solutions extends beyond individual interactions, as AI applications now play an integral role in delivering public services, democratic practices (Pham, O'Sullivan, and Mai 2023), commercial activities, and beyond, across Europe.

AI skills, in this context, are not only essential digital competencies but also encompass the ability to harness the potential of AI technologies for personal and societal benefits. However, an emerging concern is the uneven distribution of AI skills among European residents, particularly between those residing in small living areas and their counterparts in larger urban settings. This disparity in AI skills underscores a broader challenge: the existing gap between small and large living areas across Europe.

Small living areas, characterised by their unique socioeconomic and geographical attributes, face distinct challenges that include limited mobility options, inadequate broadband infrastructure, and reduced access to resources for investment. These challenges necessitate equitable distribution of human, social, and economic resources to ensure sustainable growth and well-being in these regions. Addressing the territorial divides between small and large living areas becomes not only a matter of convenience but also a crucial element in facilitating Europe's green transition and digital decade.

This paper aims to investigate the disparities in digital and AI skills between residents of small living areas and their counterparts in larger living areas across Europe. The paper also identifies their perceptions about AI including levels of trust, attitudes, and awareness. By understanding the unique challenges facing Europeans living in small areas in harnessing the potential of the AI-enabled economy, findings and implications shed some light on the ways for these regions to fully utilise AI technologies and contribute to Europe's broader goals of sustainability and digital transformation.

Background

European Digital Skills Landscape

Investing in and measuring digital skills has been a priority in the EU since 2014 (European Commission 2014). The EU has set up its own indicators of digital competence (DIGCOMP) (European Commission 2014), where five areas of information and data literacy; communication and collabo-

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ration; digital content creation; safety; and problem solving, are measured annually and biannually at the EU-level.

As of 2021, DIGCOMP data showed that 54% of people in the EU aged 16 to 74 had at least basic overall digital skills (Eurostat 2021). This statistic highlights the ongoing efforts and progress made in promoting digital literacy across the EU, while also underscoring disparities among member states. Notably, the distribution of these digital skills exhibited considerable diversity across the EU. Two front-runners were the Netherlands and Finland, where 79% of the population aged 16 to 74 displayed at least basic digital competencies. Following closely behind was Ireland, with 70% of its population equipped with these essential skills, reflecting nations that are embracing the digital age with enthusiasm.

However, on the other end of the spectrum, we find countries facing more substantial challenges in bridging the digital divide. Romania, with 28% of its population in the specified age group possessing basic digital skills, emerges as a clear outlier. This highlights the need for targeted interventions and investments in digital education to uplift underserved communities and regions. Bulgaria, at 31%, and Poland, at 43%, also faced challenges in ensuring widespread digital literacy. Factors such as access to technology, the quality of educational resources, and socioeconomic disparities can all influence these statistics.

These discrepancies in digital skills across the EU underscore the importance of continued efforts to promote digital literacy for all citizens. Bridging the digital divide not only ensures equal access to opportunities in the digital era but also empowers individuals to fully participate in the evolving digital landscape, from online education to remote work and beyond. The discrepancies in digital skills do not only exist in different countries within the EU but they do among living areas within the EU, for instance, urban or cities versus rural or smaller towns or living settings and among the two major genders of the Europeans. In the 2021 data set, 26% of the EU population aged 16-74 had above-basic digital skills. Notably, urban residents had a higher percentage (33%) with such skills compared to those in towns/suburbs (24%) and rural areas (20%) (Eurostat 2023b).

Among 26 out of 27 EU countries, urban dwellers consistently showed the highest percentage of above-basic digital skills, except in Malta, where towns/suburbs had a higher share (82%) compared to cities (Eurostat 2023b). The trend of higher digital skills in cities held true across all five aspects measured, with the largest gap seen in content creation skills, where urban residents had a 16% higher proficiency compared to rural counterparts.

Once again, throughout European Union member states, it was generally observed that a greater percentage of individuals residing in urban areas possessed skills above the basic level, as opposed to those living in towns, suburbs, or rural regions. Nevertheless, there were a few exceptions:

- Concerning individuals with advanced information and data literacy capabilities, the highest percentage in Belgium was found among residents of towns and suburbs, where 71% exhibited such skills, compared to 70% in rural areas and 68% in cities.
- In terms of advanced communication and collaboration skills, the highest proportion in Cyprus was found among those living in towns and suburbs, with 91% displaying these skills, as opposed to 88% in cities and 81% in rural areas. Furthermore, in the Netherlands, the highest percentage was observed among individuals residing in rural areas, with 94% possessing these skills, compared to 93% in towns and suburbs and 92% in cities.
- Regarding digital skills discrepancies in gender, around 52% of women in the European Union have basic or higher-level digital competencies. In contrast, girls aged 16 to 19 exhibit a notably higher rate at 70% (Eurostat 2023a). The EU nations with the highest proportions of girls possessing basic or advanced digital skills were Malta, leading the pack at 96%, closely trailed by Croatia and Finland, both at 93%, with Czechia at 89% and Austria at 87%.
- Conversely, the lowest percentages were recorded in Germany and Romania, both standing at 47%, followed by Bulgaria at 51%, Italy at 59% and Luxembourg at 60%.
- The data indicates that the percentage of girls with basic or higher-level digital skills surpasses that of the entire population in all EU member states, except for Luxembourg (64% of all individuals compared to 60% of girls) and Germany (49% compared to 47%).
- In 15 EU member states, the disparity between the percentage of girls with basic or advanced digital skills and the percentage of all individuals is 20 percentage points or more in favour of girls.

AI Skills and Perceptions among European Public

Measuring and understanding AI skills and perceptions among the European public are in its infancy. The latest available data was captured in the "Special Eurobarometer 516 European citizens' knowledge and attitudes towards science and technology", which included some attitude measurements toward AI (European Commission 2021). In the Eurobarometer survey, involved 26,827 individuals from all 27 EU Member States, 29% of respondents believe that AI and automation will create more jobs than they will replace. The outlook is least optimistic for new technologies in AI, with only 61% with a positive view.

However, most respondents in every EU Member State anticipate a positive impact of AI over the next two decades. Particularly high levels of optimism are observed in Malta (79%), Portugal (77%), Belgium, and Ireland (both 70%). Conversely, the lowest levels of optimism are found in Romania (49%), Austria (53%), and Slovakia (54%). The most enthusiastic respondents, who believe there will be a 'very positive' effect, hail from Malta (38%), Portugal (29%), Italy, and Cyprus (both 25%). Men tend to hold more positive opinions about the impact of various technological advancements on life in the next two decades compared to women. For instance, 66% of men believe AI will have a positive impact, compared to 57% of women.

Additionally, individuals aged 15-54 are more inclined than their older counterparts to anticipate the positive effects of AI and other advanced technologies. The analysis reveals that residents of towns are more likely to have positive views regarding the impact of new technologies including AI. For example, 64% of those in larger towns believe that new technologies in AI will have a positive impact, while this figure stands at 55% for those residing in rural villages.

In a separate survey carried out in 2021, more than 4,000 respondents from eight EU countries shared their awareness, attitudes, and trust in AI (Scantamburlo et al. 2023). Approximately 49.5% of the participants indicated they possessed minimal or no knowledge on the subject, whereas only 20.9% believed their knowledge to be at an advanced or expert level. When evaluating the overall sentiment towards AI, nearly 64% of the respondents expressed approval of AI. The concept of leveraging education to boost public trust garnered strong support, with 71.4% favouring this strategy; universities and research centres are seen as more trustworthy than national governments in ensuring responsible AI use.

Despite the widespread integration of AI applications and algorithms like voice assistants, chatbots, and search engines into the daily routines of many Europeans, there is a notable scarcity in the comprehension and assessment of their AI skills. While the EU's digital skills are fundamental for the effective utilisation of digital tools, it is equally imperative for the public to possess the capability to identify when they are engaging with AI systems, be it on their mobile device or computer, and to discern when a decision or recommendation is being generated by an AI system. Additionally, they must acquire the ability to evaluate the accuracy of these recommendations and decisions (O'Sullivan 2022).

European Living Areas

European living areas comprise mega-cities, large cities, small and medium-sized cities, and rural areas. Most of the cities are considered urban areas/regions of large, small, and medium-sized ones. Small urban areas play a crucial role in Europe's social, economic, and territorial landscape, serving as hubs for essential services and offering a high quality of life. These areas, typically housing between 5,000 to 50,000 residents, are diverse and lack a universally accepted definition. Nonetheless, they are home to approximately 43% of the EU population, even when excluding areas with low population density (Böhme et al. 2022).

The EU is currently undergoing a period of significant transition marked by demographic changes, climate change, and digitalisation. Demographic shifts are impacting these areas, with some experiencing population growth while others face decline and ageing populations. Furthermore, approximately 34% of the EU population lived in shrinking regions in 2020, and this trend is expected to continue, with around 51% of the EU population predicted to live in such regions by 2040. Migration patterns, especially among young families, are contributing to stability or growth in urban cores within these shrinking regions.

Notably, support and attention have historically favoured large cities as drivers of innovation and development, leaving small urban areas in peripheral regions with fewer resources. This neglect has resulted in declining services, natural degradation, cultural heritage loss, and weakened governance structures, exacerbating territorial inequalities.

Thus, small urban areas are vital components of Europe's landscape, but they face diverse challenges and require investment and support to address these issues, particularly in the context of demographic shifts, climate change, and digitalisation. Residing in those small urban areas are their residents, who share the challenges but at their personal levels, including their digital and AI skills and other demographic factors including gender, education level and age.

Europe is actively putting its Digital Decade plan into action while simultaneously working towards meeting its obligations related to the United Nations' Sustainable Development Goals. Among the critical benchmarks to gauge progress within the Digital Decade framework, European digital skills indicators carry substantial significance, reflecting the European Union's vision for embracing digital transformation. The Digital Compass has established an ambitious objective for the year 2030: to ensure that 80% of individuals aged 16 to 74 in the EU have either basic or advanced digital skills.

Hypotheses

The relevant work reviews show that there are numerous gaps in both baseline understanding of European digital and AI skills and the empirical evidence for precision development and implementation of relevant policies and investments in addressing them. Thus, a few hypotheses were generated to shed some light on where and how the pertinent policies and investments would yield the best possible results in addressing the digital and AI skills for Europeans in their corresponding living areas:

- Hypothesis 1: There are differences in AI awareness, attitudes, and trust in AI solutions and entities between the people living in small areas and their peers in larger living areas.
- Hypothesis 2: People living in small areas have lower levels of self-reported digital and AI skills than their peers in larger living areas.
- Hypothesis 3: Age, gender and education levels have relationships with AI awareness, attitudes, and trust in AI solutions and entities between the people living in small areas and their peers in larger living areas.
- Hypothesis 4: AI and digital skills have relationships with AI awareness, attitudes, and trust in AI solutions and entities between the people living in small areas and their peers in larger living areas.

These hypotheses are comprehensive in the way they are formulated. For analyses to generate enough evidence and or data rejection or acceptance of the hypotheses, there are first layer of analyses to be done and those analyses can be more detailed hypotheses themselves. Thus, the method section will explain how the analyses and statistical tests are being done for this paper.

Research Methods

Questionnaire and Survey Method

The questionnaire and survey data were adopted from (Scantamburlo et al. 2023), which contains a collection of respondents to 14 question items based on three dimensions of trust, awareness, and attitudes in the use of AI applications, along with demographic information, living areas and self-assessed digital and AI skills. The survey was conducted through online interviews with an average completion time of 20 minutes from June 2021. The respondents' information was anonymised and processed in compliance with the EU's General Data Protection Regulation (GDPR). More details on data collection and questionnaire design are available (Scantamburlo et al. 2023).

The Likert scale items in the questionnaire ranged from 1 to 5, with 1 representing more negative values such as "not at all", "never", "not important at all", and "strongly disapprove", and 5 representing more positive values such as "a lot", "always", "very important", and "strongly approve". The 5-point Likert scale is widely utilised in social science to examine human attitudes and perceptions (Nunnally 1994), and ensures that the items were straightforward and comprehensible (Likert 1932; Biasutti and Frate 2017).

In the scope of this paper, we only consider the relevant surveyed data for the Likert-scale questions, i.e., a question that contains multiple Likert sub-items, about AI Awareness (Q7), AI Attitude (Q8), Trust in AI Solutions (Q12), Trust in Entities (Q14). Summaries of these questions with their Likert sub-items can be seen in Table 1. Additionally, we used demographical variables (i.e., age, gender, education) along with self-assessed digital skills and AI skills to conduct the hypotheses tests.

Statistical Analysis Methods

First, we assess the questionnaire's item robustness and theoretical dimensions by conducting both an Exploratory Factor Analysis (EFA) and a Confirmatory Factor Analysis (CFA). The sample (n=4,006) was randomly equally divided into two groups: n_1=2,003 for EFA and n_2=2,003 for CFA. Note that only items measured on the Likert scale were utilised in the EFA and CFA analyses. Prior to conducting the EFA, we evaluated the sample adequacy using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity (Kaiser 1974; Fabrigar et al. 1999). A good threshold is KMO $\geq$ 0.7. For Bartlett's test of sphericity, a significant result (p-value $<$ 0.05) indicates that the data are appropriate for factor analysis (Kaiser 1974; Fabrigar et al. 1999). To evaluate the internal consistency of the EFA, we used Cronbach's α ($\alpha > 0.8$), which is recommended as the most suitable coefficient for ordinal-type scales (Gadermann, Guhn, and Zumbo 2019; Zumbo, Gadermann, and Zeisser 2007). We also assessed the validity of the factor structure obtained through EFA using CFA. The CFA was conducted by utilising a polychoric matrix and the diagonally weighted least squares (DWLS) extraction method, which is considered more appropriate for ordinal data than other extraction methods (Li 2016).

After the factors had been identified and assessed from the previous analyses, we employed bivariate analysis to explore whether there are significant relationships between the factors and relevant variables (i.e., demography and self-assessed digital and AI skills variables). We conducted non-parametric tests, i.e., Mann-Whitney U (Mann and Whitney 1947) and Kruskal-Wallis H (Kruskal and Wallis 1952), as the data was not assumed to be Normally distributed. The Mann-Whitney U test is a non-parametric test that compares the median of two independent groups (Mann and Whitney 1947) while the Kruskal-Wallis H test compares the medians of more than two independent groups (Kruskal and Wallis 1952). All data processing and statistical analysis tasks were conducted in R version 4.3.0 (with stats packages) and Python (with the Scipy and Pandas libraries).

Analysis Result

Questionnaire Data Validation

Regarding the suitability of data for conducting EFA, the KMO = 0.96, indicates that the data is highly suitable for EFA. Similarly, Bartlett's test of sphericity's p-value $<$ 0.0001, further confirms the suitability of the data for EFA. These findings are consistent with prior research suggested by (Kaiser 1974; Fabrigar et al. 1999).

Four factors were identified through the use of parallel analysis (Lim and Jahng 2019), i.e., AI Awareness, AI Attitude, Trust in AI Solutions, and Trust in Entities (see Table 1). The factors were able to explain 62% of the overall variance and were extracted based on their factor loading. Note that items with factor loading less than 0.50 were excluded, and the remaining items were categorised into a single factor based on their highest load.

In order to evaluate the discriminant validity, we examined the factor correlation matrix, which indicated that all four factors showed positive correlations. Moreover, none of the correlation coefficients exceeded the threshold of 0.7, which indicates that the factors derived from EFA exhibited satisfactory discriminant validity. To evaluate the reliability of our questionnaire, all Cronbach's α values $>$ 0.8 indicate good internal consistency (see Table 1).

Next, we conducted a CFA to assess the proposed factorial structure of the questionnaire data. Our CFA results showed that the EFA model had acceptable fit indices, with RMSEA = 0.011, CFI = 0.995, TLI of 0.994, SRMR = 0.03, and a p-value $<$ 0.0001. The CFA result supports the reliability and validity of the survey data, which is important for ensuring that the obtained analysis results are accurate and meaningful (Kline 2023).

Bivariate Analysis

The bivariate analysis revealed noteworthy insights regarding respondents residing in different areas with different population sizes and the four factors identified from the EFA and CFA analysis. Particularly, as can be seen in Table 2, there were no significant differences in AI Awareness and AI Attitude between individuals inhabiting small-size and large-size areas, as indicated by Mann Whitney U tests p-values $>$ 0.05. However, a significant difference emerged in

Cronbach's alpha	α	Factor loadings
Factor: Trust In Entities - Trust in entities that may ensure a beneficial use of AI (Q14_1 - Q14_6)	0.88	
Q14_1. National Governments and public authorities		0.78
Q14_2. European Union (including European Commission/European Parliament)		0.74
Q14_3. Universities and research centres		0.55
Q14_4. Consumer associations, trade unions and civil society organisations		0.65
Q14_5. Tech companies developing AI products		0.66
Q14_6. Social media companies		0.78
Factor: Trust in Solutions - Importance of specific policy measures to increase trust (Q12_1 - Q12_6)	0.9	
Q12_1. A set of laws enforced by a national authority which guarantees ethical standards and social responsibility in the application of AI.		0.84
Q12_2. Voluntary certifications released by trusted and competent agencies which guarantee ethical standards and social responsibility in the application of AI.		0.73
Q12_3. Having independent expert entities that monitor the use and misuse of AI in society, including the public sector, and inform citizens.		0.82
Q12_4. The adoption and application of a self-regulated code of conduct or a set of ethical guidelines when developing or using AI products		0.78
Q12_5. The provision of clear and transparent information by the provider that describes the purpose, limitations and data usage of the AI product		0.84
Q12_6. The creation of design teams promoting diversity and social inclusion (e.g. gender wise, different expertise, ethnicity, etc) and the consultation of different stakeholders throughout the entire lifecycle of the AI product		0.61
Factor: AI Awareness - Awareness of the application of AI in different sectors across Europe (Q7_1 - Q7_10)	0.927	
Q7_1. Healthcare (e.g. diagnostic support, personalised medicine)		0.75
Q7_2. Insurance (e.g. fraud detection, personalised risk assessment)		0.79
Q7_3. Agriculture (e.g. robotic harvesting, crop optimisation)		0.79
Q7_4. Finance (e.g. fraud detection, loan decision support systems)		0.79
Q7_5. Military (e.g. automated weapons, cybersecurity for data protection)		0.71
Q7_6. Law enforcement (e.g. predictive policing to forecast areas where crime is likely and dispatch police units)		0.80
Q7_7. Environmental (e.g. climate prediction, energy harvesting forecast)		0.74
Q7_8. Transportation (e.g. self-driving vehicles)		0.73
Q7_9. Manufacturing industry (e.g demand forecasting, robotics)		0.72
Q7_10. Human resource management (e.g. CV screening, workforce planning)		0.79
Factor: AI Attitude - Attitude towards the application of AI in specific sectors (Q8_1 - Q8_10)	0.93	
Q8_1. Healthcare (e.g. diagnostic support, personalised medicine)		0.75
Q8_2. Insurance (e.g. fraud detection, personalised risk assessment)		0.82
Q8_3. Agriculture (e.g. robotic harvesting, crop optimisation)		0.73
Q8_4. Finance (e.g. fraud detection, loan decision support systems)		0.85
Q8_5. Military (e.g. automated weapons, cybersecurity for data protection)		0.69
Q8_6. Law enforcement (e.g. predictive policing to forecast areas where crime is likely and dispatch police units)		0.85
Q8_7. Environmental (e.g. climate prediction, energy harvesting forecast)		0.78
Q8_8. Transportation (e.g. self-driving vehicles)		0.63
Q8_9. Manufacturing industry (e.g demand forecasting, robotics)		0.77
Q8_10. Human resource management (e.g. CV screening, workforce planning)		0.66

Table 1: Lists of latent factors with their items derived from EFA and CFA analysis.

	N	Trust in Gov Entities	Trust in AI Solutions	AI Awareness	AI Attitude
Mann–Whitney U		**p-value = 0.03**	**p-value = 0.02**	p-value = 0.08	p-value = 0.1
Small population-sized	1731	□: 3.68, △: 3.74	□: 3.91, △: 4.00	□: 3.57, △: 3.70	□: 3.64, △: 3.70
Large population-sized	2156	□: 3.74, △: 3.78	□: 3.98, △: 4.00	□: 3.62, △: 3.70	□: 3.68, △: 3.80

Table 2: Bivariate analysis results between the identified factors and respondents living in different population-sized areas. □ - Mean; △ - Median

	Trust in Gov Entities	Trust in AI Solutions	AI Awareness	AI Attitude
Residents from small population-sized areas ($< 30,000$ **people**)				
Education level	***	***	*	***
Gender		*		
Age group	*	***		
Digital skills	***	***	***	***
AI skills	***		***	***
Residents from large population-sized areas ($\geq 30,000$ **people**)				
Education level	***	***	*	***
Gender		*		
Age group	**	***		**
Digital skills	***	***	***	***
AI skills	***		***	***

Table 3: Bivariate analysis results between demographic and identified factors in respondents from small and large population-sized areas. * = p-value $< .05$, ** = p-value $< .001$, *** = p-value $< .0001$, empty value = not significant (p-value $> .05$).

Trust in AI Solutions and Trust in Entities when comparing respondents from small-size and large-size areas, with Mann Whitney U tests p-values < 0.05. Furthermore, it was observed that individuals in small population-sized areas tend to have lower levels of Trust in both AI Solutions and Entities, implying a possible area-specific divergence in perceptions towards artificial intelligence. [**H1 partly supported**]

Regarding the analysis of (self-assessed) digital and AI skills, no significant difference was observed in self-assessed AI skills between individuals residing in different population-size areas, with a p-value $= 0.5$. However, a significant contrast emerged in self-assessed digital skills, with a p-value < 0.0001. This difference suggests that respondents from smaller population-size areas tend to evaluate their digital skills lower in comparison with those from larger population-size areas. [**H2 partly supported**]

Based on the preceding results, we conducted a more detailed analysis by splitting the survey data into two distinct subsets: respondents residing in small populations (less than 30,000 people) and those in large populations (30,000 people or more). Within each subset, bivariate analyses were performed between the identified factors and demographic variables for Hypothesis 3, as well as self-assessed skills for Hypothesis 4 (see Table 3).

With respect to demography variables, both subsets of the survey data show a consistent relationship between the four identified factors and education levels and gender. Across all education levels, significant differences were observed in all four factors, indicating that respondents with higher levels of education tend to hold more positive views concerning AI Awareness, AI Attitude, Trust in AI Solutions, and Trust in Entities (Kruskal Wallis H tests' p-value < 0.0001). Regarding gender, however, the analysis merely revealed a noteworthy difference in the Trust in AI Solution factor, with Mann Whitney U tests returning a p-value < 0.05 between male and female groups.

Additionally, in the context of age groups, a significant difference was observed in Trust in AI Solutions and Trust in Entities among respondents from small population size areas (Kruskal Wallis H tests' p-value < 0.05). This pattern can also be seen in larger population size areas, where similar results were found, along with an additional significant difference in AI Attitude. [**H3 partly supported**]

Furthermore, both subsets yielded similar outcomes in the bivariate analysis concerning the four factors and self-assessed skills. Particularly in both subsets, all four factors show a significant difference between respondents with high and low digital skills, with Mann Whitney U tests p-values $<$ 0.0001. Regarding the distinction between individuals with high and low self-assessed AI skills, significant variations were observed in AI Awareness, AI Attitude, and Trust in Entities, although no significant difference was found in Trust in AI Solutions. [**H4 partly supported**]

Discussion

In H1, the data do not allow for a full rejection of the hypothesis: "There are differences in AI awareness, attitude, trust in AI solutions and entities between the people living in small areas and their peers in larger living areas." From a comprehensive view, there were no statistically notable differences in terms of AI Awareness and AI Attitude when comparing individuals residing in small population-sized and large-sized areas. This might come from the fact that AI is a new topic for all Europeans (European Commission 2021).

However, a contrast emerged concerning Trust in AI Solutions and Trust in Entities between respondents from these two distinct living environments. This difference in trust levels points to a regional variation in how people perceive and interact with AI. In particular, it is observed that individuals living in small population-sized areas tend to have lower levels of trust in both AI Solutions and Entities when compared to their counterparts in large-sized areas. This outcome implies that there may be specific factors at play in smaller communities that contribute to a higher degree of scepticism or caution when it comes to embracing AI-driven solutions and trusting the entities behind them. It might come from a "disconnect from public AI policies" and "poor engagement with AI education and training" (Scantamburlo et al. 2023) and a set of laws, which the AI Act is setting (European Commision 2021), with compliance and governance structures, would improve the levels of trust among all Europeans in AI solutions and applications, especially in the public services. To better understand this phenomenon, it is essential to explore the potential reasons behind this divergence in trust.

In H2 "People living in small areas have lower levels of self-reported digital and AI skills than their peers in larger living areas" was partly rejected by the data. There was a notable absence of substantial differences in how individuals assessed their AI skills, regardless of whether they lived. However, a significant divergence emerged when it came to self-assessed digital skills. This discrepancy implies that individuals residing in smaller population-size areas tend to rate their digital skills lower compared to those living in larger population-size areas.

This finding confirmed the difference in digital skills based on geographical location such as urban and rural areas detected in (European Commission 2021). The finding validates questions about the factors that might contribute to the contrast in self-assessment while highlighting differences in access to digital resources, educational opportunities, or exposure to technology (Gaffikin 2019).

H3 and H4 were conjectured to detect more granular understandings among the demographic variables, e.g., age, gender and education levels and their AI and digital skills in association with their AI awareness, attitude, trust in AI solutions and entities between the people living in small areas and their peers in larger living areas.

From deeper analyses of the two distinct groups, data do not allow for full rejection of the raised hypotheses. Specifically, within both subsets, all four factors show significant differences between respondents with high and low levels of digital skills. Regarding the difference between individuals with high and low self-assessed AI skills, we noted significant variations in AI Awareness, AI Attitude, and Trust in Entities. However, no substantial difference emerged in Trust in AI Solutions. Hence, Hypothesis 4 received partial support in this context.

Regarding the demographic variables, both subsets of our data consistently revealed associations between the four identified factors and education levels as well as gender. Across all educational backgrounds, we observed significant differences in all four factors, indicating that respondents with higher levels of education tended to hold more favourable opinions about AI Awareness, AI Attitude, Trust in AI Solutions, and Trust in Entities. However, regarding gender, our analysis unveiled a noteworthy difference solely in the Trust in AI Solutions factor, suggesting that gender had a limited influence on other facets of AI perception.

Regarding the age groups, we identified significant differences in Trust in AI Solutions and Trust in Entities among respondents from small population size areas. This pattern was also apparent in areas with larger population sizes, where similar results were observed. Additionally, an extra significant difference emerged in AI Attitude in larger populations. This finding partially supports Hypothesis 3.

The findings in age-related and gender-related variables influence digital skills and AI perceptions and their demonstrated consistent associations between education levels and the four factors related to AI, confirming those outcomes found in (European Commission 2021).

There is now a clearer need to formulate policies and projects addressing those digital and AI skill gaps, especially for those in small living areas. While there are numerous EU-wide digital skills improvement programs with sizeable associate funding, it is a must to provide targeted support, e.g., specifically designed programmes, for groups of seniors, females, and those who did not finish college. For instance, seniors can learn digital skills in their own community environment such as daycare centres where seniors come to have daily activities with their peers. They can learn about AI via their engagement with robots and other voice assistant devices in those centres or similar settings.

Conclusion

This research brings some empirical evidence that guides policy implications, and practical intervention programs in addressing digital and AI skills gaps in European small size and larger living areas.

The findings show that the small size living areas have the identified challenges from the previous studies. However, with the introduction of AI solutions and applications in almost all aspects of life for Europeans, be it in workplaces, public services, or personal activities, those living in small living areas have added challenges. If those challenges are not dealt with they will hinder or amplify the challenges not only for those people but also for those small living areas, which provide alternatives for those who want to live close to nature while enjoying decent public services and amenities.

Comprehensive investment in education and awareness initiatives is essential at EU-wide, national, and regional levels to elevate perceptions, digital and AI skills, particularly among vulnerable groups such as seniors and females in small living areas. Ensuring inclusion is paramount, leaving no one behind and affirming AI's universal benefit for all.

Acknowledgements

This research has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreements No. 825619 (AI4EU) and 952070 (VISION), and from Science Foundation Ireland under Grant number 12/RC/2289-P2 (the Insight the SFI Research Centre for Data Analytics), which is co-funded under the European Regional Development Fund. This research was also conducted with the financial support of ADAPT Core under Grant Agreement No. SFI/13/RC/2106_P2 at the ADAPT SFI Research Centre at Dublin City University. The data collection and processing for this research was supported by Ca' Foscari University. This work reflects only the authors' view and the European Commission is not responsible for any use that may be made of the information it contains.

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