On the way to Industry 5.0? Analysing the relationship between attitudes regarding AI and material deprivation in Hungary

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Industry 4.0 technological development is ongoing and has changed the role and nature of the human factor during work through various processes. In response to this, the concept of Industry 5.0 would develop a human-centred approach to technological development. Industry 5.0 is not a new concept, but its potential effects are not yet identifiable. Nevertheless, during technological development, complementary and substitutive effect can prevail from employees' perspectives; therefore, omission from employment can cause differing levels of deprivation. The primary focus of this study is analysing the relationship between material deprivation and individuals' attitude towards technological development. To do so, we conduct econometric analyses regarding demographic, territorial and material deprivation using a database from a representative micro-level questionnaire survey. The results reveal a weak negative relationship between income as a proxy variable of material deprivation and technological development in Hungary. Regarding demographic factors, younger age groups and those with higher education are less fearful of technological development, primarily artificial intelligence (AI). Regional development, regardless of whether it is settlement-, county- or regional-level development, also significantly influences attitudes, and people living in more developed Hungarian regions and larger settlements are less afraid of AI.

Keywords:

industry 5.0,
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relationship analyses,
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Introduction

In recent years, technological development of Industry 4.0 has permeated economic life and everyday life in various forms. Individual technological achievements began to have a significant role as a complementary and substitutive factor in individuals' various activities. From an economic perspective, while these changes can have effects on the labour market and productivity, the effects can differ depending on the nature of the activity, the position and the complexity of work processes. In general, individuals have experienced relevant changes in work and everyday life from technological development. However, these transformations are unbroken and shows an ever-accelerating tendency that can generate further effects in an exponential manner.

The significant impact of technological change on human work and life resulted in the creation of the concept of Industry 5.0, which refers to introducing a human-centred approach (and according to many definitions related to sustainability) to new technological achievements. Such technological transformation cannot solely be a quantitative factor, nor can it be measured only using productivity surplus or increased efficiency. The role of the human factor and its relation to certain dimensions of technological development must also be examined. The Industry 5.0 approach is not a new concept, but it has been characterised by heterogeneous definitions. Therefore, it is essential and essential to synthesise and systematise existing approaches and identify the main factors, effects and mechanisms.

The human factor of technological development is multifaceted, and the relationship between individuals and technology can also be identified as a bidirectional causal relationship. As a result, the qualitative and quantitative factors of human capital have an impact on technological adaptation (e.g. through wage costs), and different levels of technological progress can influence labour market. The close relationship between the two factors entails the negative consequences of being unable to take part and different degrees of deprivation. Deprivation can be influenced by many factors such as individuals' education, attitudes towards technology, related usage habits, regional factors and/or material deprivation. This study examines the relationship between material deprivation and individuals' attitude towards technological development (concerning artificial intelligence [AI] in particular). To do so, we identify the main characteristics with representative micro-level questionnaire research and quantitative analyses. Our research questions include is individuals' income related to their attitude towards AI and related negative associations of resentment or fear? Does a relationship exist between regional factors (settlement, location in a county or region) and attitudes towards AI? Do demographics affect attitudes towards technology? The results are consistent with previous research and theoretical conjecture. However, with the current level of technological development, individuals primarily experienced positive benefits of the widespread technological achievement. Therefore, even if people harbour a negative attitude towards technology, they do not yet perceive the relationship as connected with deprivation. As such, even micro-level quantitative examinations do not reveal this potentially powerful relationship.

Literature review

From Industry 4.0 to Industry 5.0

In recent decades, technological development and Industry 4.0 have had a significant impact on everyday life and economic processes. Labour market has partially changed, and further changes are underway and expected in the future. Industry 4.0 innovation to mass production will upend industrial patterns of designing, making, shipping and selling, emphasising logistics management, decentralisation, self-regulation and efficiency as its primary objectives (Hofmann–Rüsch 2017). Wang et al. (2016) argued that the goal of Industry 4.0 should be to combine high-tech methods with the rapid progress that machines and tools have made to improve on a global level and increase industrial productivity. Popkova et al. (2019) asserted that the transition to Industry 4.0 is a distinct industrial revolution that has been marked by the complete exclusion of human intervention in production processes, universal automation, worldwide industrial relationships and rapid changes in specific sectors. Olsen–Tomlin (2020) contended that Industry 4.0 can synthesise physical and digital systems in real time, shifting from traditional trade-offs between cost, flexibility, speed and quality that are typically experienced in manufacturing and agriculture sectors. Tail-ending technologies such as additive manufacturing, Internet of Things (IoT) sensors, networked robots and high-level AI are enablers of this revolution.

The new era of Industry 5.0 is unlike the technology-focused Industry 4.0 era. The focus of Industry 5.0 is the interaction between machines, intelligent systems and humans (Espina-Romero et al. 2023, Kovari 2024).[1] Nahavandi (2019) also noted that Industry 5.0 emerged in response to the challenges posed by the introduction of digital components and AI into production, offering a manufacturing environment in which robots complement human work that improves production. Industry 5.0 includes bringing back human involvement in industrial processes and ending the circumstance in which the role of humans in society is being pushed into the background by technological processes. This indicates that Industry 5.0 considers the needs of society and improves humans' quality of life (Saniuk et al. 2022). Industry 5.0 marks a zealous pursuit of technology that caters to human well-being. Purposeful human placement not only ensures that technological advancements will benefit society but also advances universal value, producing results that exceed mere productivity or profitability enhancement (Schwab 2016). Mourtzis et al. (2022)

[1] Sustainability is another pillar of Industry 5.0 that promotes a shift towards circular production methods that are kind to Mother Nature and maintain resource conservation (EC 2020).

contended that Industry 5.0 can build upon Industry 4.0's efficiencies with human-centric technologies and services to establish a society that is resilient and ecologically responsible. Zizic et al. (2022) emphasised the crucial role of the workforce in evolving from Industry 4.0 to 5.0, emphasising a move for human-centred production and evaluating companies' readiness for this transition. In this new paradigm, workers are not marginalised but empowered by being re-skilled and trained to work alongside sophisticated machines. Greater human intuition combined with increased machine precision can potentially generate tremendous creativity, innovation and problem-solving skills to industrial production. The advantages of Industry 5.0 will be complex and overlapping, affecting production, societal and ecological landscapes. For example, the inherent personalisation and resilience of Industry 5.0 systems may produce a wide variety of new product markets resulting in more advanced technological development (Kagermann et al. 2013). Maddikunta et al. (2021) argued that the optimal manufacturing solutions of Industry 5.0 will emerge from the harmonious combination of human intelligence and advanced machinery, with technologies such as edge computing and blockchain marking advancing such development. Akundi et al. (2022) predicted that personalised manufacturing combined with increased social involvement in manufacturing will be indispensable features of Industry 5.0, highlighting such crucial elements as supply chain enhancement, innovation at the enterprise level, smart manufacturing and the interaction of humans and machines. Ivanov (2023) considered Industry 5.0 as a new technology that advocates for synergy, mechanisation and eco-consciousness, with abundant potential for generating flexible and varied value and promoting human health across operations and supply networks. Finally, Alves et al. (2023) noted that a focal objective of Industry 5.0 is enabling workers to extend their capabilities through collaboration with digital technologies, along with an expectation to launch production systems that are suitable for sustainability and adjustment.

Cases in which machines oversee routine work and people apply creativity and strategy to the decision-making process are often beyond reach for contemporary automation and AI (Breque et al. 2021). In the context of Industry 5.0 human workers' idiosyncratic capabilities such as creativity, judgement and complex problem solving are acknowledged, and these skills are combined with machine reliability and analytical abilities (Decker et al. 2017). This setting calls for people to guide and enhance robots and AI capabilities at every stage. As such, workers could use technology to extend their own potential rather than replace it and perhaps later develop types of businesses that meet market needs using technology without people being sidelined. Moreover, the structure of work assignments could change, establishing roles that exploit human beings' capacities and enhance people's experiences at work in a way that positively boosts their contentment and mental well-being. Collaboration between humans and machines in Industry 5.0 will also stimulate innovation by creating tailor-made solutions and objects. Marrying strategic purposes with machine precision can enable enterprises to satisfy individual customer requirements, opening fresh markets and prospects without a loss of economic efficiency (Frank et al. 2019). Such commonalities could spark the rebirth of individual production, giving consumers new creative roles in the development process. Nevertheless, it should be emphasised that the identification of the factors to verify the effectiveness of Industry 5.0 and the related impact mechanisms have not yet been empirically supported (Ghobakhloo et al. 2024).

A regional approach to Industry 5.0

Industry 4.0 has also had considerable impact on regional-level productivity and labour markets. Its effects also highlight the need for Industry 5.0 at the regional level. This can occur in different ways; for example, involvement in local economic development, reducing regional differences through specific technological development and shrinking regional distance at micro level. Nevertheless, negative consequences can also arise if certain regions' exclusion intensifies and widespread disengagement occurs.

Moreover, Industry 5.0 introduces a potential to shift towards local manufacturing, which would reduce the current environmental impact of freight transportation and logistics chains. Schwab (2016) noted that regions must contribute towards establishing educational systems that are oriented towards existing populations to cultivate professional groups to accommodate the future technology era. Differences in economic power and technological capabilities between regions may form a foundation for this division. Regions blessed with sophisticated infrastructure and strong investment capabilities will be able to achieve benefits from Industry 5.0 more swiftly, leaving others to clamber along behind them to catch up. Accordingly, regional policies could negate imbalanced growth between all communities as they transition to a new advanced industrial model that would provide opportunities to secure the territory, bringing together industries and people to advance common prosperity (Breque et al. 2021). As Industry 5.0 evolves, each region must adjust industrial policies to meet and respond to current needs and circumstances. Regions can reshape their economic futures by establishing an environment that combines local capabilities and global skills. Industry 5.0 contrasts with traditional industry by combining local characteristics and taking advantage of global technological advances to promote affluent, sustainable futures for all communities. This transition is not merely a small change but an essential transformation in which regional dynamics establish the foundation for achieving success. Furthermore, it is essential to ensure that undeveloped regions benefit from the fruits of technological progress as efficiently as possible, which requires that adequate infrastructure is in place (Sachs 2005). Sectoral considerations have identified the electronics sector as a key Industry 5.0 sector (Espina-Romero et al. 2023).

In addition, it must be emphasised that the spread of Industry 4.0 achievements and the concept of Industry 5.0 may affect individual regions differently. Lagging behind on technological development or different regions' involvement at different levels can expand the differences between individual regions. (It should be also emphasised that this can be a positive influencing factor as it can help a lagging region catch up.) Underdevelopment and exclusion of individual regions and sub-regions can occur at macro and micro levels. Small businesses can also experience disadvantages of technological development if they are unable to take advantage of its advantages. Such exclusion can reinforce various forms of deprivation that can appear in different ways and can be strengthened by Industry 4.0 technological development and can also be mitigated through the human-centric nature of Industry 5.0. If individuals lack access to adequate information regarding the effects of modern technologies, negative feelings towards technology can arise (Saniuk et al. 2022), resulting in technology deprivation. However, for the proper application of Industry 5.0, it is essential to understand individuals' attitude towards deprivation. Technological development can be correlated with several types of deprivation, the two most significant of which are social and material deprivation. This study is concerned with the latter based on its economic nature as it is essential to examine the relationships between Industry 5.0 and material deprivation.

Relationship between Industry 5.0 and material deprivation

New technologies hold great promise for increasing economic prosperity and societal progress. However, left untreated, the lag in leveraging technological advances can only widen existing socio-economic gaps and consign entire communities to permanent poverty. Strategic administration of technological progress is imperative for reducing poverty and driving innovation. Emerging technologies' potential to serve as catalysts for modernisation and social advancement while also pushing the continuing development of society forward is like a double-edged sword. Technological evolution primarily reduces poverty by raising productivity and lowering costs. Work that requires considerable human labour tends to be increasingly automated with technological advances and has historically reshaped the agricultural workforce into industrial and services-based labour. This process is consistent with Schumpeter's (1942) idea of 'creative destruction'. The widespread dissemination of information and communication technologies (ICTs) has made a substantial impression on poverty reduction, while mobile banking services that are being used in places that have no established financial institutions stand out as premier examples. ICTs make it possible for people to connect with the national economy and reach markets beyond their own locales, with considerable advantages (Jack–Suri 2011).

Furthermore, access to ICTs drives education and skills improvement, which are vital for moving people out of poverty by broadening their horizons and enhancing job prospects (UNESCO 2023). Conversely, new technology can raise the threat of deepening poverty. A '*digital gap*' may well emerge between those with technology access and those without. Worldwide, countries have differing capacities and infrastructure to extract full value from technological breakthroughs. Therefore, poorer communities can be increasingly left behind (Norris 2001). This trend was likely more pronounced in the wake of the Covid-19 pandemic as a similar relationship was already detectable before the pandemic. Technology and financial development increase inequality for most emerging economies, while the effects for advanced economies are mixed (Gravina–Lanzafame 2021). Heterogeneity has also been demonstrated in empirical studies. Examining Türkiye, Cetin et al. (2021) found that technological innovation positively affects income inequality in the country, while economic growth is negatively linked with income inequality. Technological change and human capital distinguish skilled and unskilled workers, resulting in rising inequality and influencing economic growth. In contrast, Wahiba–Dina (2023) examined a database of African countries between 1992–2019, finding that technological change and human capital distinguish skilled and unskilled workers, which increases inequality and influences economic growth. However, Afzal et al. (2022) demonstrated a positive relationship between income inequality and technology in low-income countries, determining that technology reduces poverty. Inequality caused by technology can reduce efficient resource allocation and increase poverty by making technology access a determining factor (Mirza et al. 2019). In contrast, Antonelli–Gehringer (2017) found that the spread of technology can reduce income inequality in economies with high income inequality.

One channel through which technology influences income and wealth is the labour market. Changes in the share of labour employed in high-tech sectors is the main driver of an inverted U-shaped relationship between income inequality and economic development (Castaldo–Bonis 2023). Furthermore, the spread of automation and AI means that jobs, particularly those for low-skilled workers, run the risk of disappearing (Acemoglu–Restrepo 2020). Autor (2015) clarified that automation-induced displacement threatens routine, intermediate skill jobs. Goos–Manning (2007) advanced the skill-biased technical change hypothesis, arguing that technological progress favours workers with more advanced skills and competencies. However, the pace of information technology development demands increased specialised skills in the workforce in a race with accelerating professional demands. Those equipped with needed skills are more likely to adapt to new tech-centric work environments, but those without such skills can find themselves helpless and unemployed without the possibility for improvement. In addition to wages, Green (2012) noted that technological development also affects job security, working conditions and career advancement prospects. Job polarisation exacerbates class income inequality, and technology surges spread to those who are at the vanguard to adopt advanced technologies; therefore, jobs further divide between different labour segments (Goldin–Katz 2008). Highly skilled workers achieve benefits from reciprocal dynamics with technology and are required to imagine, guide and cooperate with new systems. However, those with fewer skills live in the shadow of mechanisation, competing with less expensive, labour-saving machines. With its rapid technological advances, globalisation also contributes to the offshoring of high-wage, low-skill local jobs, expanding job divisions more clearly. As a result, low-skilled workers must either upgrade their skills or be content with low-paying work (Blinder 2006).

The labour market relationships of technological development related to individuals' education also presents the possibility of deprivation, which can arise on many levels such as absolute and relative, social and material deprivation and can also exacerbate existing deprivation. Material deprivation in contemporary times can be traced back to Townsend (1979), who proposed the relative deprivation approach. Material deprivation cannot be directly observed but it can be identified through the deprivation of various material goods (McKnight et al. 2024) and is closely related to households' income (Espina-Romero et al. 2023, Gábos et al. 2016). According to Eurostat's (2024) definition, material deprivation is evident when three of the following factors can not apply to a given individual: 'to pay their rent, mortgage or utility bills, to keep their home adequately warm, to face unexpected expenses, to eat meat or proteins regularly, to go on holiday, to have a television set, to have a washing machine, to have a car, to have a telephone'. These factors appear in different regions as different measures in various periods, and in the case of social groups. Furthermore, technological development has a clear impact on the labour market and income development and is also a measure of material deprivation. This highlights two significant factors. The human-centredness of Industry 5.0 can be a relevant aspect for mitigating material deprivation, and it is essential to examine the connections between antipathy towards technology and material deprivation. The above statement concerning relevant factors is particularly true for regional level analyses of Hungarian territorial characteristics. It can be challenging to measure deprivation at the regional level, as micro data are needed.[2] Data from EU statistics on income and living conditions (EU-SLIC) at the regional level are extremely limited. We use these data within the framework of the empirical analyses of this study to examine whether a relationship is evident between technological development and material deprivation (and their proxy variables). Furthermore, the study also examines whether a relationship is evident between Hungarian demographic conditions and territorial differences and attitudes related to technological development.

[2] Despite this, some attempts have been made to construct a Hungarian regional deprivation index; see Koós (2015) for more details.

Empirical analyses

As previously established in the theoretical relationships discussion, the focus of the concept of Industry 5.0 as well as sustainability is human-centredness. In other words, Industry 5.0 endeavours to counterbalance the technology-centred approach of Industry 4.0 and resulting individual deprivation. The previous studies identified above have established that the potential effect is valid even when the achievements of Industry 4.0 are applied. However, due to the potential effects of technological development on the labour market, material deprivation can have a particularly significant role, and in this context, affect individuals' fear of new technology and willingness to adapt. In addition, rapid, continuously changing technological development can strengthen individuals' sense of deprivation. In accordance with these findings, the primary aim of this study is to analyse the relationship between material deprivation and individual attitudes towards technological development (particularly AI) in Hungary. Notably, AI is closely related to Industry 5.0 and can be considered a key element of the relationship between humans and robots (Espina-Romero et al. 2023). The rapid integration of AI across businesses emphasises the need to understand social perspectives and the elements that influence AI acceptability. These elements include trust, perceived hazards, cultural differences and socio-demographic factors that have significant influence on how AI is perceived and implemented. Trust is a key factor for shaping societal acceptance of AI, particularly in high-risk sectors such as healthcare and self-driving cars. However, social perceptions can be influenced by dangers of employment displacement and ethical concerns (Gerlich 2023). Perceived utility and simplicity of use are consistent determinants of AI acceptability, and user performance and perceived effort expectations have a significant correlation with AI acceptance. The link between functionality, trust and perceived humanity also influences acceptance, particularly in AI virtual assistants (Kelly et al. 2023, Zhang et al. 2021). Cultural variables also have a significant influence on AI acceptability, with preferences for human engagement varying across regions. People in economically developed nations with good digital skills are more open to AI, while concerns about job displacement are more prominent in less developed economies. Age, gender and socio-economic level also impact people's perceptions towards AI. Younger people and those with higher education or technological capabilities are more likely to accept AI technology (Vu–Lim 2022, Méndez-Suárez et al. 2023). Social anxiety over AI's influence on employment, particularly in automation-prone industries, has been well documented. The anticipated threat of job loss and limited decision-making power contributes to societal opposition to AI, and strong governance and transparent communication tactics are needed to increase AI's acceptability (Vu–Lim 2022). These findings emphasise the use of AI and the related attitudes as a proxy variable. We also examine other factors that may be related to attitudes towards technological achievements.

This includes, for example, the relationship with demographic conditions or territorial (regional or county level) examinations.

Data and methodology

Data in the international databases are limited for our analysis. This is also true for the research factors of material deprivation and technological development, as well as AI, which makes it difficult to quantify them with a proxy variable. The most recent data (for 2023) in the Eurostat database are only available at the country level. At the NUTS 2 and NUTS 3 level, these are extremely limited in terms of territorial units and time limits. Another limitation of macro-level studies is the lack of adequate, accessible data for Industry 5.0 as well as the use of technological achievements.

Based on the above relationships, macro-level studies can only produce limited results. Furthermore, it is more appropriate to examine the concept of Industry 5.0 using a micro-level database, starting from its change of approach. Therefore, we use a micro-level database of questionnaire responses that includes a representative sample of 1,013 respondents for our investigations. Regarding the Hungarian population over 18 years of age, the sample can be considered representative in terms of gender, age, education, type of settlement and region. We selected a random sample and collected the data between 10 February 2023 and 6 March 2023, using an omnibus research methodology. The questions used in the analyses were measured on nominal or ordinal scales. Different approaches were applied to examine the individual variables based on the nature of the scales. When the relationship between two variables measured on a nominal scale was analysed, cross-tabulation analysis, the chi-square test and the Cramer's V indicator were used. The value of the Cramer's V indicator falls between 0 and 1, where 0 determines the independence of the variables, while 1 determines complete dependence. For examinations between nominal and ordinal variables, we applied the Kruskal–Wallis non-parameters test, which determines whether a statistically significant relationship exists between two or more groups of an independent variable or between a continuous or ordinal variable. The test is not sensitive to the assumption of normality, which was also an important factor for its application. We used a double criterion for two indicators measured on an ordinal scale. In the case of the latter, we used the gamma indicator during the cross-tabulation analysis, and after the data were measured on a Likert scale, we also used Spearman's correlation coefficient. The gamma indicator reveals the relationship between two ordinal variables, the value of which is between 0 and 1, where the interpretation of dependence and independence is similar to the Cramer's V indicator. The Spearman rank correlation index also examines the relationship between the two variables, the value of which can be between −1 and 1, where similar to the gamma index and Cramer's V indicator, full dependence is indicated by values closer to [1]. This last consideration (using gamma and Spearman indices in the analyses) was made to ensure the robustness of our results. For the variables measured on two ordinal scales, the two tests produced the same results in all cases. The questions used, related abbreviations, corresponding measurement scales and the most significant descriptive statistics are presented in Table 1. The reason for missing data compared with the number of items in the entire sample is that the answer options for each question included the option of not knowing or not answering and were included as missing data in the database. We used SPSS to conduct the analyses.

Table 1

Summary of the variables used in the analysis

Question	Abbreviation	Scale of measurement	Obs.
Age group	Age	Ordinal (1–6)	1,013
Sex	Sex	Nominal	1,013
Educational attainment	Edu	Ordinal (1–4)	1,013
Type of settlement	Settl	Nominal	1,013
County	County	Nominal	1,013
Region	Region	Nominal	1,013
How do you think people's lives will change with the spread of smart devices?	Smart_1	Ordinal (1–3)	915
How much do you agree with the statement that I like to try new technology?	Smart_2	Ordinal (1–3)	1,006
How much do you agree with the statement that I have an aversion to using technological solutions that I am not familiar with?	Smart_3	Ordinal (1–3)	1,004
How much do you agree with the statement that I do not want to miss out on new smart solutions?	Smart_4	Ordinal (1–3)	984
Do you agree that the next 20–30 years will bring the rise of AI?	AI_1	Ordinal (1–3)	921
Do you agree that it won't be possible to control and restrain AI if it becomes widespread?	AI_2	Ordinal (1–3)	904
Do you agree that people who can't use AI will be at a significant disadvantage?	AI_3	Ordinal (1–3)	914
Do you agree that if AI decides things, it could be a problem because we do not know how the machine thinks, and on what basis it decides?	AI_4	Ordinal (1–3)	915
Do you agree that if AI spreads in the world, people will be left behind, and the opinions and interests of each person will not be important?	AI_5	Ordinal (1–3)	924
Do you agree that machines with the help of AI will displace people from the workplace?	AI_6	Ordinal (1–3)	930

(Table continues on the next page.)

(Continued.)

Question	Abbreviation	Scale of measurement	Obs.
How afraid are you that the next 20–30 years will bring the rise of AI?	AI_7	Ordinal (1–3)	956
How afraid are you that it won't be possible to control and restrain AI if it becomes widespread?	AI_8	Ordinal (1–3)	957
How afraid are you that people who can't use AI will be at a significant disadvantage?	AI_9	Ordinal (1–3)	947
How afraid are you that if the AI decides things, it could be a problem because we do not know how the machine thinks and on what basis it decides?	AI_10	Ordinal (1–3)	958
How afraid are you that if AI spreads in the world, people will be left behind, and the opinions and interests of each person will not be important?	AI_11	Ordinal (1–3)	955
How afraid are you that machines working with the help of AI will displace people from the workplace?	AI_12	Ordinal (1–3)	957
How informed do you feel about AI?	AI_13	Ordinal (1–5)	999
What is the net (after tax) monthly income of your household?	Income	Ordinal (1–12)	620

Source: authors' editing based on the questionnaire.

Results

Demographic and spatial relationships of attitudes towards technology

In addition to examining material deprivation and attitudes towards AI, it is also essential to conduct some supplementary examinations. Such micro-level studies can contribute to expanding the approach to the human-centred concept of Industry 5.0 by identifying domestic characteristics along demographic and territorial relationships in terms of attitudes towards AI. In the case of the AI variables, demographic and territorial variables were also examined. However, Table 2 only presents the three most significant results based on the research question.

Based on the Kruskal–Wallis test results, several conclusions can be made regarding demographic and regional considerations. From a demographic perspective, a clear difference in the negative attitude towards AI is evident across age groups. This clearly arises in the case of the elderly, where the median value for the over 70 age group was the highest for all three questions. No gender differences are revealed in attitudes towards AI. Our assumptions regarding education are also confirmed, revealing that those with lower educations (eight or less years of primary school educations or lower education in our case) are more fearful of the negative effects of AI. In terms of demographic trends, younger age groups and those with higher education are less afraid of AI. Regional relationships also confirm our previously expected results. Regarding the type of settlement, the main differences are revealed for big cities (county seats and cities with county rights) and Budapest. At the regional level, the Northern Great Plain and Northern Hungary stand out among the regions, indicating that individuals in those parts of the country they are more fearful of AI and its negative effects, while this fear is lower in the territorial units of Western Transdanubia, South Danube and the Southern Great Plain. Among the counties, Vas county is the least afraid of negative AI returns, while Borsod-Abaúj-Zemplén, Csongrád-Csanád and Szabolcs-Szatmár-Bereg counties are the most fearful. Based on the median values, Hajdú-Bihar and Nógrád counties are also loosely related to this. Notably, and particularly in the county comparison, regardless of the question, Borsod-Abaúj-Zemplén, Csongrád-Csanád and Szabolcs-Szatmár-Bereg counties all pull homogeneously in the same direction, while the other counties vary depending on the nature of the question and how the respondent perceived the negative consequences to the question. Concerning regional trends, regional development, regardless of whether it is settlement-, county- or regional-level development also significantly influences attitudes, and people living in more developed regions and larger settlements appear to be less afraid of AI.

We also conducted additional examinations to broaden the perspective of the analysis. Regarding awareness of AI (*AI_13*), the generational difference stands out more strongly, and the elderly have heard much less about AI, which is particularly true for those over 70, but the age group between 60 and 69 also shows a clear difference. In terms of information, people living in village and city settlement types are less informed compared with those in Budapest. Considering regions, the Western and Southern Danube and the Southern Great Plain can be considered less informed, which is also the cause of significant differences. The county data fit the regional data, mirroring the fear of AI above. To expand the focus from AI only, we also include respondents' attitude towards technological achievements in the empirical analysis. No significant differences are evident for trying new technologies at the regional level. However, a difference is found for counties, indicating that residents in Győr-Moson-Sopron county prefer to try out new tools. Similar to the county-level analysis, no differences are identified for settlement type. A difference is evident in terms of gender, indicating that all individuals prefer to try new technological devices. The results are similar to the findings above in terms of age groups and generational differences. Overall, the results can be considered robust, and correspond to the theoretical relationships.

Table 2

Summary of the Kruskal–Wallis test results for 3 main questions

Independent variable	Significance	Evaluation
Dependent variable: AI_9: How afraid are you that people who can't use AI will be at a significant disadvantage?		
Age	0.000	A significant difference is evident between individual age groups, revealing that people become more afraid of AI as they age.
Sex	0.188	We reject the null hypothesis as no differences are evident.
Edu	0.003	Significant differences are revealed for those with secondary education, and those with eight or less years of primary education.
Settl	0.002	A significant difference is evident, which highlights the differences between big cities and Budapest and between villages and big cities.
County	0.000	Significant differences are primarily limited to Vas county (with differences from 11 other counties), but differences are also evident for several other counties, indicating differences between Csongrád-Csanád, Borsod-Abaúj-Zemplén and Szabolcs-Szatmár-Bereg counties.
Region	0.000	Significant differences are evident between the Northern Great Plain and Central Hungary, the Northern Great Plain and Western Transdanubia and Northern Hungary and Western Danube.
Dependent variable: AI_11: How afraid are you that if AI spreads in the world, people will be left behind and the opinions and interests of each person will not be important?		
Age	0.000	Significant differences are evident between individual age groups, indicating that people become more afraid of AI as they age.
Sex	0.077	We reject the null hypothesis.
Edu	0.009	Significant differences are evident for those with secondary education and those with eight or less years of primary education.
Settl	0.002	Significant differences are revealed between big cities and Budapest and between villages and big cities.
County	0.000	Significant differences are primarily limited to Vas county (with differences from eight other counties), but differences are also evident for several other counties, indicating differences between Csongrád-Csanád, Hajdú-Bihar and Szabolcs-Szatmár-Bereg counties.
Region	0.005	Significant difference is evident between the Northern Great Plain and Western Transdanubia.
Dependent variable: AI_12: How afraid are you that machines working with the help of AI will displace people from the workplace?		
Age	0.000	Significant differences are evident between the individual age groups, indicating that people become more afraid of AI as they age.
Sex	0.115	We cannot reject the null hypothesis.
Edu	0.004	Significant differences are evident for those with secondary education, and those with eight or less years of primary education.
Settl	0.004	Significant differences are revealed between big cities and Budapest, and between villages and big cities.
County	0.000	Significant differences are primarily limited to Vas county (with differences from eight other counties), but differences are also evident for several other counties, revealing differences between Csongrád-Csanád, Hajdú-Bihar and Szabolcs-Szatmár-Bereg counties.
Region	0.001	Significant differences are evident between the Northern Great Plain and Central Hungary and the Northern Great Plain and Western Transdanubia.

Income and technology

This study examines the relationship between material deprivation and attitudes towards technological development (with particular regard to AI) in Hungary. Material deprivation includes many factors; however, low income has a close correlation with relative and material deprivation (Berthoud et al. 2004). Material deprivation is fundamentally determined based on income. Lower disposable net income can limit households' financial and consumption capabilities, posing a higher risk of material deprivation, and income levels below a certain threshold can lead to exponential material deprivation. Furthermore, relative deprivation can also be influenced by income levels. Therefore, income is a characteristic and predictive factor of material deprivation.[3] In parallel, we used net monthly income as a proxy variable for material deprivation and combined with the results for demographic and regional correlations, our hypothesis is that people with lower incomes are more fearful of the negative returns of technological development (in this case: AI). As a result, the concept of Industry 5.0 and making technological development more human-centred has more relevance for low-income individuals. The results are summarized in Table 3.

Table 3

Relationship test based on cross-tab analysis and Spearman's correlation coefficient

Variables	Gamma		Spearman's correlation coefficient	
	value	significance	value	significance
Smart_1	−0.292	0.000***	−0.272	0.000***
Smart_2	−0.445	0.000***	−0.431	0.000***
Smart_3	0.120	0.005***	0.116	0.004***
Smart_4	−0.433	0.000***	−0.420	0.000***
AI_1	−0.216	0.000***	−0.197	0.000***
AI_2	−0.053	0.238	−0.052	0.196
AI_3	−0.115	0.013**	−0.106	0.008***
AI_4	−0.045	0.337	−0.047	0.240
AI_5	−0.101	0.027**	−0.094	0.019**
AI_6	−0.054	0.252	−0.051	0.206
AI_7	−0.304	0.000***	−0.264	0.000***
AI_8	−0.322	0.000***	−0.289	0.000***
AI_9	−0.297	0.000***	−0.266	0.000***
AI_10	−0.290	0.000***	−0.259	0.000***
AI_11	−0.355	0.000***	−0.314	0.000***
AI_12	−0.299	0.000***	−0.267	0.000***
AI_13	0.401	0.000***	0.378	0.000***

Notes: the variable in column (1) was paired with the income variable in all cases. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

[3] We acknowledge that many other factors besides income can influence material deprivation.

To ensure the robustness of our findings, gamma index and Spearman's correlation results are also provided. The two methodological approaches produce similar results in terms of the significance, sign and order of magnitude of the strength of the relationship. Three of the questions regarding AI attitudes do not exhibit a significant relationship with income, thus indirectly with material deprivation. The common feature of these questions is that they were not primarily directed towards deprivation but about the nature of AI (e.g. regarding the restraint and thinking of AI and the displacement effects on the labour market). However, these factors do not have a direct impact and do not directly influence individuals' attitudes. As a result, preferences are evenly distributed across individual income categories. However, the results concerning significant relationships were significantly more prominent in the responses. Regarding AI, the direction is clearly negative based on the results. However, due to the opposing logic of answering the question groups, their interpretation must be divided into two parts.[4] Among the individual AI-related statements (AI_1–AI_6), all of the significant statements refer to the spread and use of AI. The negative sign of these questions suggests that respondents with higher incomes who likely know and have used AI agree more with its potential spread, effects and risks. This is closely related to the responses concerning the fear of AI question group (they are aware of its possibilities and limitations) and is also supported by the question on AI familiarity (A_13). Regarding the fear of AI (AI_7–AI_12), as the income categories rise, antipathy towards AI and fear of related negative consequences decreases. This indicates that low-income individuals who have been more exposed to material deprivation due to the spread of AI are afraid of further deprivation, which depending on the questions can cover both absolute (for example, the spread of AI, AI_8), relative deprivation (for example, those who cannot use AI may be at a significant disadvantage, AI_9) or further aggravate material deprivation (for example, through the displacement effect on the labour market, A_12). Examining the strength of the relationship, the gamma indicator's value is spread between −0.101 and −0.355 among the significant variables. A weak, negative relationship is revealed for most indicators, and a similar conclusion can be drawn from the Spearman's correlation coefficient, where the indicator ranges between −0.094 and −0.314. Overall, a weak, negative relationship is demonstrated between income and attitudes towards AI. Based on this applied analyses, the baseline results can be considered robust. Among the indicators related to attitude, recognition of AI (*A_13*) was highlighted, indicating a positive relationship between the two variables. The results also reveal that AI recognition is higher for higher income categories. This suggests that AI familiarity can improve individual attitudes. This statement is supported by the results concerning smart devices and technological achievements, which also indicate a weak, negative relationship with income. At the same time,

[4] In the case of questions AI_1–AI_6, 1 meant completely agree and 3 meant disagree. In contrast, for questions AI–AI_12 1 meant not afraid of it at all, and 3 meant very afraid of it.

aversion to unknown technology has a positive, weak relationship with income, according to which those with higher incomes also consider new technology with reservations. Nevertheless, these findings should be treated with caution, and further future research must be conducted on this topic.

Robustness tests

We next conduct additional econometric examinations to ensure the robustness of our baseline results. The purpose of these tests is twofold as in addition to verifying the robustness of the results, we also endeavour to identify more sophisticated relationships in the modelling. The initial methodological approach of the analyses is ordered logit regression. In this context, we analyse how individuals' development of preferences in the field of various statements and questions related to AI is influenced by previous independent variables. Due to the nature of the measurement scale, ordinal variables (*Edu*, *Age* and *Income*) were also included in the analyses. The *Sex* variable was also included, and we introduce interaction terms to increase the sophistication of our model. In addition to the variables' measurement scale, using the ordered logit model is also justified by the number of elements in the sample. Differences between logit and probit models disappear for large samples; therefore, the general conclusions that can be drawn from them are not affected by the type of model or the normality of the error term. Based on these methodological considerations, the basic ordered logit model is as follows:

$$AI\_X = \beta_0 + \beta_1 Edu + \beta_2 Income + \beta_3 Age + \beta_4 Sex + \varepsilon \quad (1)$$

where AI_X denotes the questions related to different attitudes towards AI as a dependent variable, Edu denotes the education level, $Income$ represents income, Age indicates age groups, Sex denotes gender and ε is the error term. The assumption of multicollinearity can be identified among the conditions of the ordered logit regression. In this way, we test the existence and extent of the relationship between the independent variables and only those variables are included in the model where the correlation is appropriate. Table 4 presents the results of the ordered logit regression.

Before examining the results in detail, we must note that the AI preferences based on different statements and questions represent different perceptual approaches. Of the questions used as independent variables, the first six variables (AI_1–AI_6) represented agreement with a statement, while the connections between AI_7 and AI_12 represent fear of a given factor. This is also reflected in the nature of the answers since in the first group of questions (AI_1–AI_6), where answer option 1 represents complete agreement with the statement, while answer option 3 represented disagreement, and in the second group of questions (AI_7–AI_12) answer option 1 indicated that respondents were not afraid of it at all, while answer option 3 indicated that were extremely afraid of it. This different perceptual approach is also evident in the results of the ordered logistic regression.

Table 4

Summary of basic ordered logit regression models' results

Variables	Model 1: AI_1	Model 2: AI_2	Model 3: AI_3	Model 4: AI_4	Model 5: AI_5	Model 6: AI_6	Model 7: AI_7
Edu	−0.1272	−0.0090	−0.0966	−0.0139	−0.0675	−0.0175	−0.1793*
Income	−0.0209	0.1293***	0.0737	0.1195**	0.0506	0.1265***	−0.1130**
Age	0.0876	0.0564	0.0847	0.0809	−0.0436	0.1019*	0.2669***
Sex	−0.0545	−0.0084	0.2608	−0.0540	0.1105	0.0908	0.0499
Cut1	−1.3538**	0.1742	0.0835	0.2782	−0.6027	0.5426	−2.1529***
Cut2	1.2200**	2.2492***	2.5367	2.6216***	1.7270***	2.9944***	0.7419
Obs.	560	552	556	558	563	568	590
McFadden R^2	0.0776	0.0607	0.072306	0.0688	0.0653	0.0738	0.1229
	Model 8: AI_8	Model 9: AI_9	Model 10: AI_10	Model 11: AI_11	Model 12: AI_12	Model 13: AI_13	
Edu	0.0408	−0.0111	−0.0669	0.0368	−0.0009	0.4422***	
Income	−0.1705***	−0.1531***	−0.1211**	−0.2157***	−0.1267***	0.2638***	
Age	0.2046***	0.1917***	0.2379***	0.2347***	0.2369***	−0.3121***	
Sex	0.1185	0.1327	0.0661	0.2062	0.2532	−0.4738***	
Cut1	−1.9222***	−2.0043***	−1.7240***	−2.2571***	−1.4036***	0.8398	
Cut2	0.3768	0.4898	0.6435	0.3585	1.0421*	2.0365***	
Cut3	–	–	–	–	–	3.8877***	
Cut4	–	–	–	–	–	6.0936***	
Obs.	590	585	592	591	590	616	
McFadden R^2	0.0939	0.0979	0.0969	0.1191	0.0999	0.1709	

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Examining the results of the basic model, regardless of the question group, educational attainment cannot be considered a significant influencing variable in terms of AI attitudes. This finding contradicts the results of previous empirical analyses, motivating us to employ more sophisticated modelling approaches. However, we must first analyse additional variables of the baseline model. The income variable does not exhibit a significant effect for all questions in the first question group; however, if the significance level takes on an appropriate value, the sign of the coefficient is positive, revealing that as incomes rise, disagreement with the given AI-related statement also increases. Therefore, those with higher incomes are less likely to agree that AI will be less controllable after becoming widespread, that AI decisions can create problems in the absence of control and that AI will take away jobs than those with lower incomes. In the second group of questions on fear of AI, income clearly exhibits a significant negative effect; therefore, as income increases, respondents become increasingly less afraid of AI, its spread and effects. The results of the two groups of questions support one another regarding the effects of income, indicating that those with lower incomes and individuals threatened by material deprivation are much more fearful of AI. The age variable also exhibits notable significant values in the case of the second group of questions, revealing a negative sign implying that fear of AI increases with age. Similar to education level, sex does not have a significant effect on AI attitudes. This relationship is congruent with previous results.

To examine the more sophisticated effects of education, we introduce interaction terms into the analysis. The purpose of the interaction variable is to determine the effect of the relationship between the two examined independent variables. Therefore, we next examine whether the interactions between income and education and between age groups and education influence attitudes towards AI. We also examine the correlations between the variables based on the modelling conditions defined earlier, where a strong, significant correlation between the two interaction variables indicates that they cannot be included in one model. Therefore, to confirm that the multicollinearity condition is not violated, the following models are developed with the two interaction variables:

$$AI\_X = \beta_0 + \beta_1 Edu + \beta_2 Income + \beta_3 (Edu \times Income) + \beta_4 Age + \beta_5 Sex + \varepsilon \quad (2)$$

$$AI\_X = \beta_0 + \beta_1 Edu + \beta_2 Income + \beta_3 (Edu \times Age) + \beta_4 Age + \beta_5 Sex + \varepsilon \quad (3)$$

where the two interaction terms are $Edu \times Income$ and $Edu \times Age$. The results of the tests are presented in Tables 5 and 6.

Table 5

Summary of first extended ordered logit regression model's results

Variables	Model 1: AI_1	Model 2: AI_2	Model 3: AI_3	Model 4: AI_4	Model 5: AI_5	Model 6: AI_6	Model 7: AI_7
Edu	−0.6908**	−0.3059	−0.7731**	−0.9542***	−0.5044	−0.3522	−0.1372
Income	−0.2137*	0.0295	−0.1570	−0.1968	−0.0977	0.0161	−0.0985
$Edu \times Income$	0.0819*	0.0430	0.0982**	0.1356***	0.0632	0.0477	−0.0062
Age	0.0928	0.0613	0.0900	0.0909	−0.0387	0.1054*	0.2665***
Sex	−0.0439	−0.0019	0.2771	−0.0194	0.1216	0.1011	0.0481
Cut1	−2.5955***	−0.4576	−1.3969	−1.7398**	−1.5499*	−0.1699	−2.0638**
Cut2	−0.0103	1.6201*	1.0728	0.63119	0.7861	2.2858***	0.8316
Obs.	560	552	556	558	563	568	590
McFadden R^2	0.0801	0.0615	0.0762	0.0758	0.0669	0.0747	0.1229
	Model 8: AI_8	Model 9: AI_9	Model 10: AI_10	Model 11: AI_11	Model 12: AI_12	Model 13: AI_13	
Edu	0.0573	−0.1422	0.0998	−0.1419	0.0681	0.2971	0.0573
Income	−0.1649	−0.1977*	−0.0639	−0.2767**	−0.1029	0.2144*	−0.1649
$Edu \times Income$	−0.0024	0.0191	−0.0242	0.0258	−0.0100	0.0203	−0.0024
Age	0.2044***	0.1926***	0.2371***	0.2355***	0.2365***	−0.3109***	0.2044***
Sex	0.1177	0.1368	0.0608	0.2109	0.2513	−0.4709***	0.1177
Cut1	−1.8871**	−2.2874***	−1.3590	−2.6512***	−1.2517	0.5062	−1.8871**
Cut2	0.4119	0.2064	1.0101	−0.0362	1.1943	1.7037*	0.4119
Cut3	–	–	–	–	–	3.5595***	–
Cut4	–	–	–	–	–	5.7681***	–
Obs.	590	585	592	591	590	616	590
McFadden R^2	0.0939	0.0980	0.0971	0.1194	0.1000	0.1711	0.0939

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Table 6

Summary of second extended ordered logit regression model's results

Variables	Model 1: AI_1	Model 2: AI_2	Model 3: AI_3	Model 4: AI_4	Model 5: AI_5	Model 6: AI_6	Model 7: AI_7
Edu	0.7216***	0.1475	0.5519**	0.4376*	0.4141*	0.5012**	−0.2609
Income	−0.0174	0.1284***	0.0769	0.1201**	0.0507	0.1277***	−0.1131**
$Edu \times Age$	−0.2276***	−0.0417	−0.1745***	−0.1212**	−0.1308**	−0.1419**	0.0214
Age	0.6686***	0.1610	0.5303***	0.3883**	0.2848*	0.4577***	0.2139
Sex	−0.0634	−0.0116	0.2504	−0.0528	0.1062	0.0864	0.0493
Cut1	0.8978	0.5731	1.8006**	1.4731*	0.6487	1.8978**	−2.3675***
Cut2	3.5232***	2.6495***	4.2814***	3.8285***	2.9938***	4.3667***	0.5298
Obs.	560	552	556	558	563	568	590
McFadden R^2	0.0892	0.0611	0.0792	0.0721	0.0693	0.0784	0.1230

	Model 8: AI_8	Model 9: AI_9	Model 10: AI_10	Model 11: AI_11	Model 12: AI_12	Model 13: AI_13
Edu	0.1341	0.0616	−0.03818	0.1020	−0.1229	0.3223
Income	−0.1706***	−0.1528***	−0.1209**	−0.2153***	−0.1269***	0.2652***
$Edu \times Age$	−0.0249	−0.0193	−0.0076	−0.0173	0.0317	0.0344
Age	0.2661*	0.2394	0.2568*	0.2778*	0.1580	−0.3973**
Sex	0.1183	0.1326	0.0662	0.2057	0.2547	−0.4749***
Cut1	−1.6818**	−1.8136**	−1.6483**	−2.0847***	−1.7210**	0.5418
Cut2	0.6171	0.6801	0.7190	0.5303	0.7266	1.7383**
Cut3	–	–	–	–	–	3.5843***
Cut4	–	–	–	–	–	5.7867***
Obs.	590	585	592	591	590	616
McFadden R^2	0.0941	0.0979	0.0969	0.1192	0.1002	0.1712

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

The extended models test whether educational attainment interacts with income and age to determine whether the previous significant result was influenced by these relationships. In the first extended model (Table 5), the interaction term exhibits a significant positive relationship for only three questions. These are statements regarding the spread of AI, the disadvantages arising from the lack of AI use and problems arising from the lack of control over AI decisions. The positive significant relationship demonstrates that people with higher incomes and educational attainment agree less with these statements, indicating that they are less afraid of the negative consequences and spread of AI. However, the insignificant results for the other questions complicate this picture, requiring future examinations. This is also justified by the fact that after including the interaction term, the three models show a negative, significant result for educational attainment itself. This supports the results of previous empirical studies, according to which people with lower educational levels agree less with the above statements, exhibiting more negative attitudes towards AI. Apart from income, which does not show a significant result in the first extended model, the other variables show similar results to the baseline model. The loss of significance for income is attributable to the inclusion of the interaction term.

The gender variable does not have a significant effect, while age shows a positive significant result in the second group of questions, confirming the previous result that fear of AI increases with age.

The second extended model (Table 6) shows similar results. The income variable exhibits a similar pattern to the baseline model, indicating that as income rises, fear of AI decreases. The interaction term in this model examines the interaction between educational attainment and age. Similar to the previous interaction term, the interaction only shows a significant result for the first group of questions, exhibiting a negative sign. This implies that negative attitudes towards AI increases with increasing education and age. This can be attributed to the assumption that with advancing age, education can no longer offset negative feelings arising from technology use or a lack of knowledge. In this model, age shows a significant positive sign, similar to that of educational level. Therefore, age and education level can influence attitudes towards AI in themselves in such a way that their increase reduces negative attitudes towards AI. This leads to a partially contradictory result in the case of age, requiring the introduction of Model 13 into the analytical framework. In this model, the dependent variable is measured on an ordinal scale to determine how informed individuals feel about AI. The results reveal that age shows a negative, significant relationship in all three models, indicating that knowledge and level of awareness regarding AI decrease with advancing age. This confirms that the positive, significant relationship identified in the second extended model may also suggest a lack of awareness since individuals do not perceive the challenges of AI due to the lack of awareness. However, if the claims are presented as a threat from a rhetorical perspective, then the negative relationship with advancing age can be identified. This is attributable to individuals being much more afraid of uncertainty and uncertain factors and having a stronger negative attitude towards them. Therefore, the level of awareness may have a relevant influence on attitudes towards AI from the perspective of age groups; however, this requires further sociological and psychological research and can serve as the basis for future studies.

Conclusion

The technological development known as Industry 4.0 is ongoing. Technology has an expanding impact on work processes and everyday life and influences the role and importance of the human factor. Therefore, missing out on technological achievements or their adaptation can result in lags and competitive disadvantages at micro and macro levels. Nevertheless, it is essential to coordinate the potential benefits of technological achievements with its human side. This perspective generated the concepts of Industry 5.0 and human-centred technological development. This study identified the most important concepts of Industry 5.0 and delineated its factors, impact mechanisms, and its relationship with material deprivation. The negative effects of technological development on the human factor can increase deprivation and have a particularly large impact on material deprivation through labour market processes. Our empirical analyses conducted a representative micro survey to examine how AI, as the most popular achievement of Industry 4.0, is related to material deprivation. In addition, we analysed the relationships between AI and Hungarian demographic and territorial factors. The results reveal a weak, negative relationship between income (proxy for material deprivation) and fear of AI in Hungary. Concerning demographic factors, younger age groups and those with higher education are less afraid of AI. However, in among age groups, knowledge of AI, or even the lack thereof, can influence attitudes and fear towards in older generations. Regarding regional factors, regional (settlement-, county- or region-level) development has a considerable influence on attitudes, and people living in more developed regions and larger settlements are less fearful of AI, and the results are robust and fit into the theoretical context. The findings also emphasise that technological development necessitates the development of targeted regional industrial policies. Regional industrial policy planning can increase regional and aggregate productivity and improve competitiveness. In addition, it is essential to alter attitudes towards new technologies through training programmes. The development of targeted digital skills improvement training based on new technological developments will facilitate the application of programs that also improve lower-skilled workers' labour market competitiveness, which can narrow the digital divide, social income inequality and poverty in less developed regions. This development is further strengthened by the Industry 5.0 concept. In terms of future research directions, further micro-level measurement of different deprivation levels, and in close connection with this, measurement of the deprivation in technological achievements (whether material or due to a lack of knowledge and skills) would offer an additional perspective.

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