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Are small farms sustainable and technologically smart? Evidence from Poland, Romania, and Lithuania

Abstract
Sustainable development of farms is determined by many factors and, in recent years, significance of modern technologies and artificial intelligence (AI) has been pointed out, especially in terms of beneficial effects on economic performance and natural resources. Therefore, there is a need to answer the question about the application of AI technologies in small-scale farms, especially those with a relatively high level of sustainability. In order to obtain the information, a survey in Poland, Romania and Lithuania was carried out. Among the respondents, the 20 most sustainable farms in each country were selected using the CRITIC-TOPSIS method. Next, in-depth interviews were conducted to explore attitudes, behaviour and knowledge of AI. . The results show that small-scale farms in selected countries do not apply artificial intelligence. Although owners recognise and appreciate the benefits of AI, they are not convinced to implement this technology in their own business, they are not completely uncritical about using AI tools in the practice. The main obstacles are: low level of knowledge, misconception of the price of innovation or lack of capital for buying more advanced technology, low interest in implementing innovative solutions due the small scale of production or habituation to traditional production methods.

Keywords
small-scale farms | technology | artificial intelligence | sustainable development | interview research | farmers opinions

JEL Codes
O33, Q01, Q12, Q16, Q55

1. Introduction

Sustainable agricultural development, as defined by the FAO in 1987, consists of using natural resources and orienting technologies and institutions to meet current human needs and those of future generations (Bastan et al., 2018). This mode of agricultural development does not degrade the environment and ensures the conservation of soil, water resources, plants, and animals, all while meeting production targets and ensuring a decent quality of life for rural communities (Allen et al., 1991). Sustainable development is an objective of strategic importance in the European Union (European Commission, 2021). To date, many publications have been produced on the impact of agricultural practices on rural sustainability (e.g. Diamond, 1993; Foley, 2005; Siqueira et al., 2021). These publications point to the beneficial effects of modern agricultural technologies on increasing land productivity and labour productivity, improving the quality of natural resources, ensuring food security, reducing poverty, and more (Zha, 2020; Eli-Chukwu & Ogwugwam, 2019; Elijah et al., 2018; Mhlanga, 2021). It can be assumed that the application of modern technology using artificial intelligence (AI) contributes to the economic, social and environmental sustainability of farms. The implementation of such innovations is justified in the case of small farms, which are depreciated in the food supply chain as a result of the market mechanism, which leads to an income disparity in relation to large farms (Guth et. al., 2020; Smędzik-Ambroży et. al., 2021; Argilés, 2001; Czyżewski et al., 2019). The use of artificial intelligence solutions can improve their financial performance. On the other hand, some authors indicate that the adaptation of innovative solutions in small farms may be hampered by a lack of knowledge, skills, and capital (Cook & O'Neill, 2020; Tanghe, 2021; Renda et al., 2019).

The aim of this publication is to assess the level of use of modern technologies (namely artificial intelligence) in smallholder farms in Poland, Romania and Lithuania. These are three European Union countries, belonging to the so-called post-Soviet block, with a fragmented agrarian structure as a result of a similar path of systemic transformation. This study included units with a relatively high index of economic, social and environmental sustainability. Thus, the authors ask if there is a synergy between sustainability and the degree of adaptation of modern technologies. At the same time, the rationale for using innovative solutions, and the barriers associated with it, are indicated. This makes it possible to formulate recommendations for agricultural policy regarding the implementation of artificial intelligence in the smallholder sector. The article uses a qualitative research approach – in-depth interviews with farm owners, which are less commonly used in the literature – to explain the phenomenon. The questions and statements found in these interviews fit into the theory of reasoned action (TRA), which is a psychological theory that links beliefs to behaviour. This approach includes the following components of human behaviour: knowledge, subjective norms, and individuals' behavioural intentions. It is assumed that behavioural intention is the most proximal determinant of human behaviour (Azjen, 1985; Fishbein & Ajzen, 2010). To the best of our knowledge, there are no similar studies for Central and Eastern European countries; hence, it is reasonable to conclude that the article fills a research gap in this area. The article is structured as follows: Part 2 describes the literature review, Part 3 presents the data set and methods, Part 4 includes results and discussion, and the final part deals with conclusions.

2. Literature review

Artificial intelligence (AI) refers to human-designed computer systems and tools that observe the environment, collect and interpret data, process the information, and decide on the best action to achieve a given goal. AI uses algorithms to develop solutions that mimic the behaviour of nature or humans (Samoili et al., 2020). Many definitions refer to innovative technologies (machines) that use a kind of intelligence to behave like humans (Nilsson, 1998; Russel & Norvig, 2010). Artificial intelligence has revolutionized information technology in many areas, such as data mining, machine learning, computer vision, evolutionary computation, and fuzzy logic (Zhang et al., 2014).

Agriculture is one of the sectors of the economy that uses AI achievements (Adhitya et al., 2020). Here, the application of modern technologies began as early as the 1960s with the implementation of the Agriculture 2.0 paradigm during the period known as the 'Green Revolution'. The development of agrotechnology led to an increase in agricultural productivity and food supply on a global scale, but the revolution also resulted in negative consequences: both ecological (loss of biodiversity, disappearance of biodiversity, excessive water consumption, and abuse of chemical fertilisers and pesticides) and social (increase in income disparity and loss of food surpluses) (Pinstrup-Andersen & Hazell, 1985). These negative consequences drove a paradigm reorientation towards Agriculture 3.0, where the focus on efficiency was replaced by a focus on sustainable productivity in economic, social, and environmental contexts. In terms of technology use, Agriculture 3.0 is associated with the automation and robotisation of agricultural work such as planting, spraying, and harvesting (Ren et al., 2020; Fountas et al., 2020). 'Smart farming' turned out to be an attractive way to achieve sustainability, not least in terms of profitability.

The second decade of the 21st century is seen as the beginning of a generation of automation in agriculture referred to as Agriculture 4.0. This generation is set to meet the challenges of the future, which are linked to the scarcity of natural resources, negative climatic and demographic changes, the persistent problem of malnutrition, and food waste. Agriculture 4.0 represents the fourth revolution in agricultural technology, associated with the emergence of advanced information systems, supported by internet solutions which allow the collection of huge amounts of data related to agricultural production, such as: meteorological data, soil conditions, farmland structure, market data, and others. The processing of the collected data and the application of advanced artificial intelligence systems allow agricultural producers to make appropriate decisions, increasing productivity and leading to better economic results (Zhai et al., 2020). Besides, properly managed production processes bring environmental benefits by optimising the use of water, mineral fertilisers, and plant protection products as part of what is deemed precision agriculture (Rose et al., 2021). This approach does not rely on applying water, fertilizers, and pesticides evenly across the crop area or feeding the whole animal stock with equal amounts of feed. Instead, farmers use minimal inputs on very specific areas or use individually tailored animal feeding patterns. AI focuses on automated dosing, control, and accounting systems using analysis and synthesis of mathematical, fractal and physical metric models (Moskvin, 1998). A set of special tools is used for this purpose, including robots, temperature and humidity sensors, aerial photography, remote sensing, GPS technology, unmanned airplanes and drones, etc. Such production is supported by IT solutions based on links with artificial intelligence algorithms (Fountas et al., 2020).

An example of the application of Agriculture 4.0 technology (precision agriculture with AI) is the monitoring and control of crop pests, followed by the precise dosing of pesticides. Using a camera system, a pest infestation is detected and then the appropriate minimum dose of product is dispensed. Another method of pest control is to run an ultrasonic frequency system. These methods use such advanced technologies as GPUs (Graphics Processing Units), which are special electronic circuits designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display device. GPUs are used in systems such as embedded systems, mobile phones, personal computers, workstations, game consoles, and DBNs (Deep Belief Networks, which are a generative graphical model, or alternatively a class of deep neural network, composed of multiple layers of latent variables ('hidden units'), with connections between the layers but not between units within each layer) (Patricio & Rieder, 2018). Artificial intelligence systems also have applications in production risk management, for example, through their ability to predict crop yields, especially when there are significant fluctuations in supply due to external factors such as drought or flooding. The prediction process requires, among other things, a systematic study of many soil quality variables: pH, mineral composition, amount of organic matter, soil moisture, etc. This is done through the use of very large database mining methods (Gandge et al., 2017). Predictability of yields allows for anticipatory actions carried out by both farmers and institutions involved in supporting the agricultural sector. This type of management contributes to improved farming performance, ameliorating the economic dimension of sustainable agricultural production (Vohra et al., 2019). Yet another application of AI is the method of assessing food quality, which makes it possible to adapt the offer to consumer requirements. Computer image processing systems using multi-class detection help to segment fruits and vegetables in terms of appearance, dimensions, or weight (Mahajan et al., 2015; Lee et al., 2020).

Apart from the described environmental and economic effects, the implementation of AI in the agricultural sector raises social consequences. It is purported that the traditional image of agricultural production will be significantly changed by reducing the employment of low-skilled labour and creating new jobs related to intellectual effort. In reality, this may lead to a disruption of farmers' roles and skills (Skvortsov, 2020; Smith, 2020). The income disparity between larger and smaller farms may also widen. The latter may not benefit from the effects of modern technologies due to the costs associated with implementing innovations. Digitalisation, promoted by large agribusinesses, creates the risk of indebtedness and dependence of farmers on corporations. Farmers would be forced to buy technology that collects information, then transfer their data, and again buy them back from machine companies. These new market-oriented technologies, governed by a trend towards commoditisation and privatisation of knowledge, would increase dependence on expensive tools that small-scale farmers mostly cannot afford, accelerating their disappearance in rural areas (Ajena, 2018). Between 2005 and 2016, about one quarter of farms (4.2 million) disappeared in the European Union, the vast majority of which (ca. 85%) were small farms of a size under 5 ha (Eurostat, 2020). It can be expected that, in a free market mechanism, digital 'big data' technologies would be captured by large-scale agriculture, which would exacerbate the development inequalities between small and large players. In light of this, it makes sense to involve the state in the process of creating fair rules and investment support, so that the benefits of AI reach all agricultural producers (De Clercq & Vats & Biel, 2018). At the same time, support is needed for advisory services related to the use of AI (Yu et al., 2017), assuming that farmers (mainly smallholder farmers) are a relatively low-educated social group. With a properly constructed policy, the implementation of AI among farms, including those with small-scale production, can work in tandem with achieving the goals of sustainable agricultural development.

3. Materials and methods

3.1. Data set

As was mentioned in the introduction, small-scale family farms from three countries belonging to the European Union (Poland and Lithuania having joined in 2004, while Romania did in 2007) were included in the analysis. These countries are similar in terms of agricultural production structures and institutional environment; they have also gone through a similar path of economic transition. Different definitions were used to distinguish small farms. The literature most often points to criteria such as farmland area, economic strength, number of animals, and market participation (Guiomar et al., 2018; European Commission, 2011). For example, very small farms could be defined as those with an agricultural area of less than 2 ha or 5 ha (Lowder et al., 2016), while small farms are those with an area of up to 20 ha (Gruchelski & Niemczyk, 2016). In turn, by including an economic strength (SO[1]) classification, Eurostat and the Farm Accountancy Data Network (FADN) use the upper limit for small farms as EUR 25 thousand (FADN, 2021). In addition, to emphasise the family nature of the farms, the criterion of the dominant share of labour input of family members involved in agricultural activities has been adopted to exclude from the analysis those individuals who, while officially recognised as farmers, actually work outside agriculture. Given the above, for this research, the following criteria were adopted: utilized agricultural area up to 20 ha UAA, standard output up to EUR 25,000, and at least 75% of the family members' labour input involved in agriculture activity.

In the first stage, the analysis was based on surveys conducted in Poland in 2018 and in 2019 in two other countries. The samples numbered 710 farms in Poland, 1000 in Lithuania, and 900 in Romania. The distribution of holdings by regions is shown in Figure 1. A purposeful and random selection of the research sample was applied. Data were collected in the form of direct interviews by agricultural advisors. Questions concerned four areas: general farm features, economic and social issues, environmental aspects, and connections with the market. In the second stage, using these data, we ordered farms according to the synthetic sustainability measure (the methodology is presented in the next section). From each country, we selected the 20 most sustainable farms (the so-called 'Top-20')[2]. Among these entities, direct in-depth interviews were conducted. The selection of 20 farms in each country was dictated by the objective factor of the project budget. The interviews took place in 2020 and involved research project members and agricultural advisors. Therefore, detailed information was collected from a total of 60 farms from Poland, Romania and Lithuania. Table 1 presents the basic statistics of the analysed units.

The average area of the farms where the in-depth interviews were conducted ranged from 10.3 ha in Lithuania to 13.4 ha in Poland. More pronounced

1 The standard output of an agricultural product (crop or livestock), abbreviated as SO, is the average annual monetary value of the agricultural output at farm-gate price, in euro per hectare or per head of livestock. There is a regional SO coefficient for each product, as an 5 years average value. The sum of all the SO per hectare of crop and per head of livestock in a farm is a measure of its overall economic size, expressed in euro.

2 In Poland, 7 farms were located in the North-West, 6 in the North, 5 in Central and 2 in the South-West. In Romania, 6 farms each were located in the Central and North-West, and 4 farms each in the West and North-East. In Lithuania, 7 farms were located in West Aukstaitija, 5 in East Aukstaitija, 3 each in South Aukstaitija and South Zemaitija, and 2 in North Zemaitija.

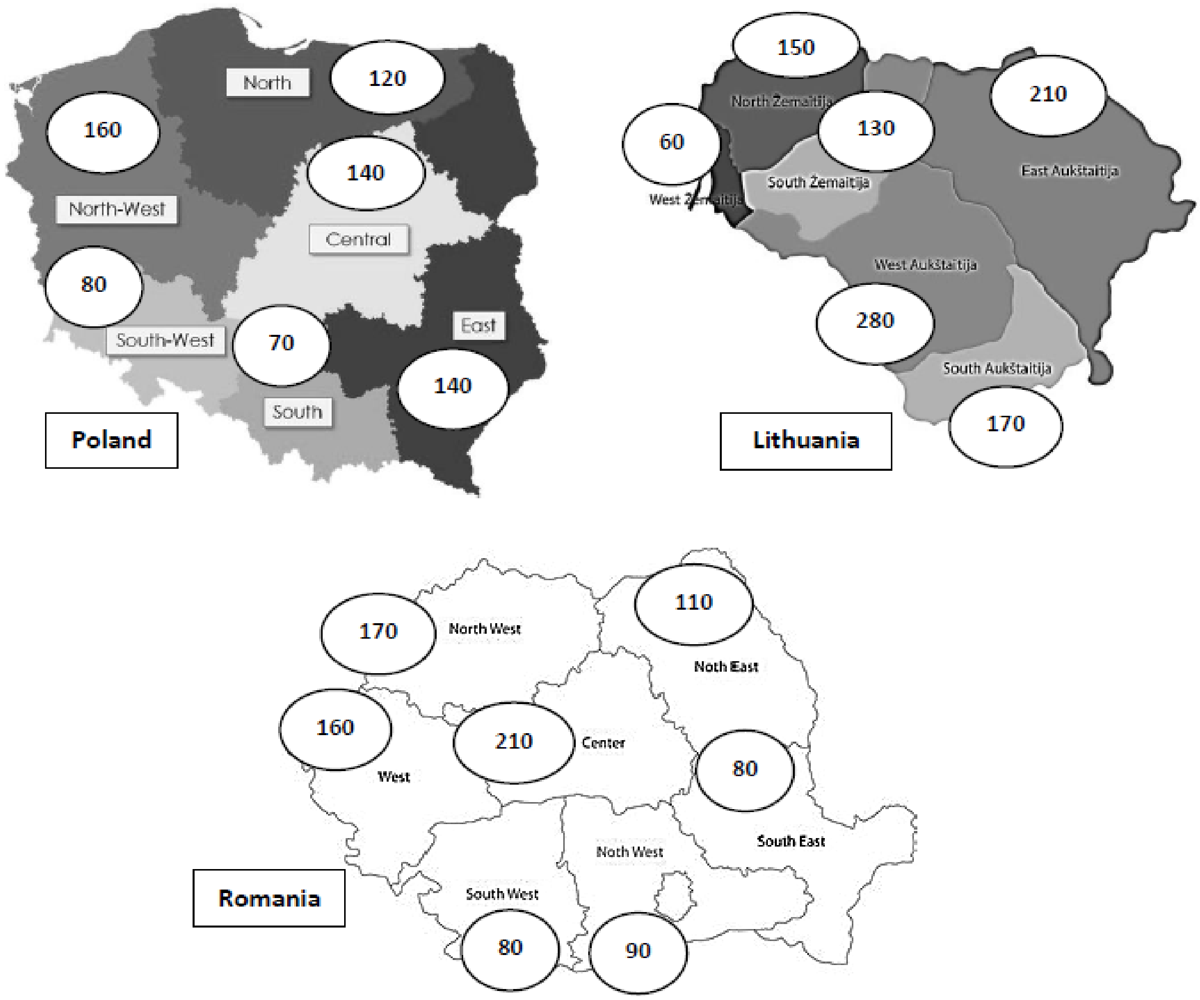

Figure 1. Regional distribution of surveyed farms for Poland, Romania and Lithuania

Table 1 . Basic statistics for the 'Top 20' farms, 2020 (values in brackets for the entire population involved in the questionnaire survey)

Farm characteristics	Average value		
	Poland	Romania	Lithuania
Farm area (ha of UAA)	13.4 (14.1)	13.2 (12.1)	10.3 (10.5)
Standard output (EUR/year)	17.905 (12.830)	12.650 (10.320)	7.501 (5.614)
Household income (EUR/month) -only from agriculture	1.917 (1.843) 1.076 (985)	1.219 (1.106) 751 (693)	1.230 (1.022) 533 (433)
Share of support in agricultural income	39% (35%)	57% (50%)	58% (55%)
Estimated farm value (thous. EUR)	209.6 (n/a)	25.7 (24.5)	51.5 (49.7)
Estimated farm liabilities (thous. EUR)	6.6 (n/a)	3.0 (2.6)	0.4 (0.5)
Age of farm manager	49 (49)	46 (47)	48 (48)
Level of education of farm manager*	4.9 (4.6)	4.8 (4.5)	5.1 (4.9)

Note: level of education in the range from 1 to 7, where 1 - no education, 7 - higher education

Source: own performance based on questionnaire survey data differences between countries can be observed in the cases of production and farm income: in Poland they were the highest, while in Lithuania they were the lowest. However, the greatest discrepancies were observed in the case of estimated farm assets. The large gap in valuation between Poland and the other two countries is due to the higher prices of land and other real estate on the Polish market (Palen et al., 2018). Interestingly, the high value of assets does not translate to the level of indebtedness of the surveyed units. It is relatively low in all countries, which confirms the risk aversion of farms (see also Theuvsen, 2013; Sulewski et al., 2020). As for demographic variables, i.e. age and education, they are similar in the three studied cases.

3.2. Methods

The study was conducted in two stages. In the first stage, a synthetic measure of sustainable development of small-scale family farms in Poland, Romania and Lithuania was determined. The base included farms among which questionnaire surveys were conducted within the research project 'The role of small family farms in the sustainable development of the food sector in the Central and Eastern European countries'. The extracted variables used for measures of economic, social, and environmental balance in the case of stimulants were subjected to zero unitisation according to Formula (1), while in the case of destimulants, Formula (2) was applied:

$$stimulant: z_{ij} = \frac{x_{ij} - min_i\{x_{ij}\}}{max_i\{x_{ij}\} - min_i\{x_{ij}\}} \quad (i = 1,2, \dots, n; j = 1,2, \dots, k; z \in [0,1] \tag{1}$$

where: $min_i\{x_{ij}\}$ – minimum value of the j function, $max_i\{x_{ik}\}$ – maximum value of the j function, i – object (farm in our case);

$$destimulant: z_{ij} = \frac{max_i\{x_{ij}\} - x_{ij}}{max_i\{x_{ij}\} - min_i\{x_{ij}\}} \quad (i = 1,2, \dots, n; j = 1,2, \dots, k; z \in [0,1] \tag{2}$$

where: $min_i\{x_{ij}\}$ – minimum value of j function, $max_i\{x_{ik}\}$ – maximum value of j function, i – object (farm in our case).

Next, weights were determined for the selected variables using the TOPSIS-CRITIC method (designation of criteria by correlation between criteria). In the TOPSIS-CRITIC method, weights are determined on the basis of standard deviations and correlations between variables. A specific feature of this method is that relatively higher weights are assigned to characteristics that have a high coefficient of variation but low correlation with other characteristics (Borychowski et al., 2020). The weights of the variables were determined according to the following formula:

$$w_j = \frac{c_j}{\sum_{k=1}^{m} c_k}, j = 1,2, \dots, m; \; c_j = s_{j(z)} \sum_{k=1}^{m} (1 - r_{ij}), j = 1,2, \dots, m, \tag{3}$$

where: c_j – a measure of the information capacity of feature j, $s_{j(z)}$ – standard deviation calculated from the normalised values of the characteristic j, r_{ij} – correlation coefficient between characteristics j and k.

The established normalised values of the variables were then multiplied by the respective weighting factors. Using the values of the variables after the weighting process, the Euclidean distances of the individual units from the development pattern and anti-pattern were calculated according to the following formulas:

$$d_i^+ = \sqrt{\sum_{j=1}^{k} (z_{ij}^* - z_{ij}^+)^2} - distance\ from\ the\ pattern \tag{4}$$

$$d_i^- = \sqrt{\sum_{j=1}^{k} (z_{ij}^* - z_{ij}^-)^2} - distance\ from\ the\ anti-pattern \tag{5}$$

where:

$$z_j^+ = (\max(z_{i1}^*), \max(z_{i2}^*), \dots, \max(z_{ik}^*)) = (z_1^+, z_2^+, \dots z_i^+)$$

$$z_j^- = (\min(z_{i1}^*), \min(z_{i2}^*), \dots, \min(z_{ik}^*)) = (z_1^-, z_2^-, \dots z_i^-)$$

The value of the synthetic trait q1 was determined according to the following formula:

$$q_i = \frac{d_i^-}{d_i^+ + d_i^-}, (i = 1,2, \dots, n) \tag{6}$$

Table 2. Variables used to determine the synthetic measure of sustainability of surveyed farms in Poland, Romania and Lithuania

Sustainability component	Variable name	Variable type*	Weight of variable for the individual sustainability component	Weight for the synthetic measure of sustainability
Economic	Income gap indicator (difference between average income in the national economy and total income of the agricultural holding)	D	0.1280	0,3304
	Subjective assessment of the household's financial situation	S	0.3398	
	Level of agricultural investment	S	0.3356	
	Estimated market value of the holding	S	0.1967	
Social	Dwelling/house furnishing index	S	0.1819	0,3089
	Usable floor area of dwelling/house per family member	S	0.0959	
	Participation in lifelong learning system	S	0.1511	
	Participation in social or cultural events	S	0.2823	
	Membership in an organisation, club, association, etc.	S	0.2887	
Environmental	Livestock Units (LSU) per ha of UAA**	D	0.1383	0,3608
	Monoculture index	D	0.2730	
	Eco-efficiency (according to DEA)	S	0.1133	
	Share of forest in the farm area	S	0.0315	
	Share of permanent grassland in the farm area	S	0.0784	
	Share of arable land covered with vegetation during winter	S	0.1992	
	Balance of soil organic matter***	S	0.1664	

Note: *variable type: S – stimulant, D – destimulant; **Livestock Unit (LSU) - is a reference unit which facilitates the aggregation of livestock from various species and age as per convention, via the use of specific coefficients established initially on the basis of the nutritional or feed requirement of each type of animal; ***Calculated according to the methodology of the Institute of Soil Science and Plant Cultivation in Pulawy, Poland as the ratio of the sum of the products of the area of cultivated plants, the mass of natural fertilizers produced, the mass of straw potentially intended for ploughing, and the corresponding reproduction or degradation coefficients in relation to the area sown on arable land in a given farm

Source: own performance based on questionnaire survey data

Table 2 presents the list of variables used in the TOPSIS-CRITIC analysis and the weights of individual elements. After determining the component measures of sustainability – economic, social, and environmental, following the adopted method – a synthetic measure of development was determined for the analysed farms. In the final part of this stage, farms were ordered according to the synthetic measure and a group of the twenty most sustainable farms was determined for further research in each country. The results obtained were used in the second stage of work.

The second stage of the research was qualitative and included in-depth interviews with the 'Top 20' farms from Poland, Romania, and Lithuania (20 in each country). The main objective of this research was to determine whether small, sustainable family farms from Central and Eastern Europe apply artificial intelligence in their operations. In-depth interviews offer a comprehensive picture of reality as perceived by the individual. They can be used to describe phenomena and to develop and test theories (Van Maanen, 1998). Therefore, the use of in-depth

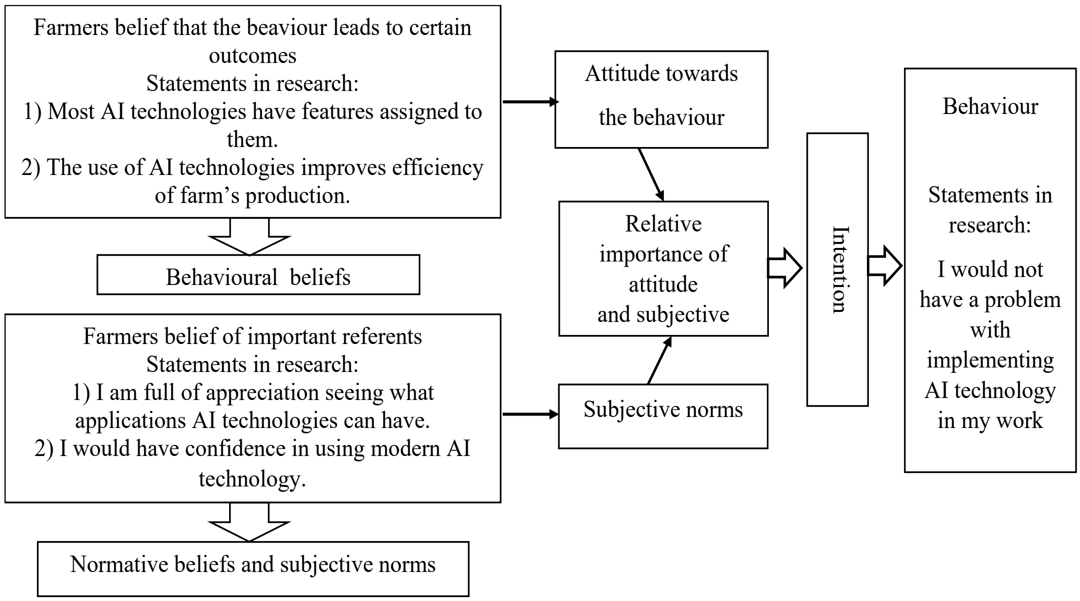

Figure 2. Statements reflecting the influence of cognitive and subjective components on the implementation of AI technologies in the interviewed farms

interviews was fully justified. It is worth noting that the implementation of this research process makes it possible to obtain information which, according to Miles (1979), is 'succinct, complete, real, creating access to causality'. Another important advantage of the interviews is that they meet the criteria of interpretative evaluation, as focused on the individual perspective, on the unit and on his/her interpretation of reality (Konecki, 2000; Denzin & Lincoln, 2000).

In the first phase of the study, a comparison was made between the attitudes of farm owners from Poland, Romania, and Lithuania regarding the use of new technologies (AI) in agriculture. For this purpose, statements concerning cognitive (knowledge), behavioural (behaviour), and emotional (attitude, norms) components were used (Aronson et al., 2005, pp. 313-315). Before conducting our research, we explained that artificial intelligence (AI) is a creative tool that simulates human intelligence and ability processes in machines, principally computer systems, robotics, and digital equipment (Patel et al., 2021). In addition, farmers were given examples and were shown photos of AI, i.e. software that uses farm data, robots such as drones, and self-driving tractors. After this introduction, it was assumed that the farmers surveyed had knowledge of AI. Farmers selected one of the following responses for each statement: 1 (totally disagree), 2 (disagree), 3 (rather disagree), 4 (rather agree), 5 (agree), or 6 (totally agree). In order to determine the differences in answers between farmers from different countries, the arithmetic mean was calculated for each country separately. It can be concluded that the higher the value of this average, the more knowledgeable the owners were about new technologies and the more favourable their attitude towards them, and their individual behaviour is manifested by the implementation of AI in their farms. The questionnaire used the following statements characterising the individual components of farmers' attitudes towards new technologies (AI):

1. Cognitive component (behavioural beliefs):

– Most AI technologies have features assigned to them.

– The use of AI technologies improves efficiency of farm's production.

2. Emotional component (normative beliefs and subjective norms):

– I am full of appreciation seeing what applications AI technologies can have.

– I would have confidence in using modern AI technology.

3. Behavioural component (behaviour):

– I would not have a problem with implementing AI technology in my work.

These statements reflected the components influencing the final behaviour of small family farm owners from Poland, Romania, and Lithuania

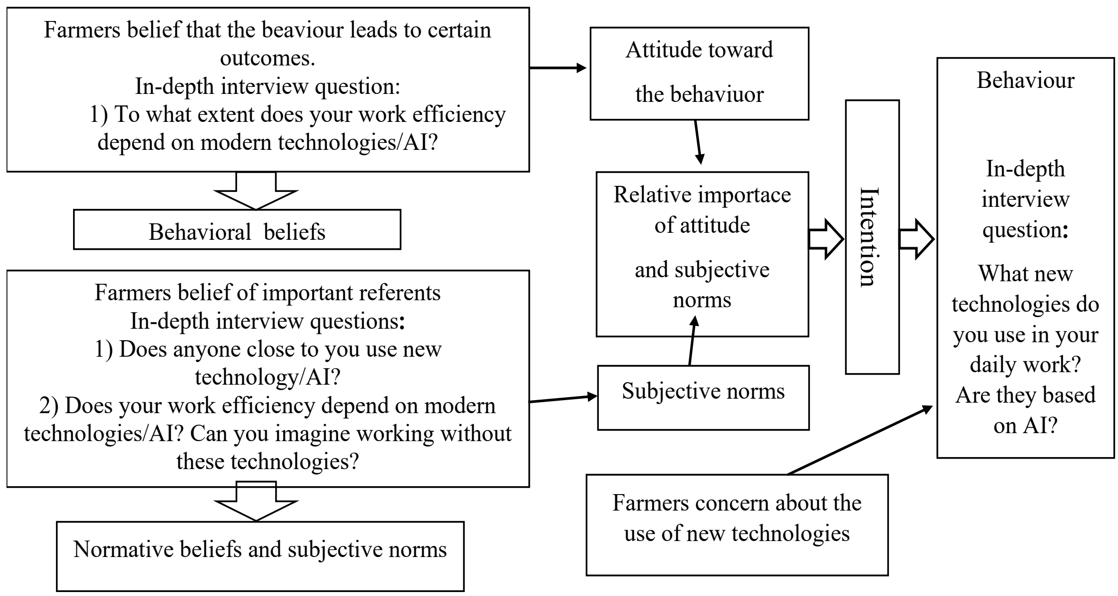

Figure 3. Questions reflecting the influence of cognitive and subjective components and opinions on the implementation of agricultural AI technologies in the surveyed farms

according to the reasoned action theory (TRA) (Azjen, 1985; Fishbein & Ajzen, 2010). The links between individual statements in the questionnaire and areas influencing final behaviour are reflected in Figure 2.

The first step was followed by a comparative analysis of the responses to questions about the use of artificial intelligence, its impact on the work of those employed on the farm, and the barriers associated with the use of these new technologies. As an in-depth interview method was used, farmers were free to speak on specific topics. The interview covered the following questions:

– What new technologies do you use in your daily work? Are they based on artificial intelligence?
– Does anyone close to you use new technology/AI?
– Does your work efficiency depend on modern AI technologies? Can you imagine working without these technologies?
– If you are not using AI, what are the main barriers/obstacles related to this?

These questions also stemmed from the components that influence behaviour as defined by reasoned action theory (see Figure 3). In addition to experience and knowledge, which determined the actions of the actors surveyed, an additional external factor was introduced into the model: fear of using new technologies.

4. Results

The best rating for the attitudes regarding new technologies (AI) was recorded by owners of small-scale farms in Poland. Farmers from Romania were in second place. The least positive notes were found among respondents from Lithuania. These notes concerned declared behaviour, knowledge, and emotions related to the application of new technologies in agriculture (Table 3). Although farmers recognise the positive features of innovative solutions, in each country, the lowest averages were obtained for statements characterising the behavioural component: 'I would not have a problem with implementing AI technology in my work'. The averages here ranged from 3.55 in Poland to just 3.05 in Lithuania. The conclusion is that the surveyed farm owners are not fully convinced about the implementation of new technologies, but they are not completely uncritical about this process. This conclusion, especially in the case of Lithuania and Romania, is strengthened by the rather low mean values for the statement: 'I would have confidence in using AI technology' (3.25 and 3.65 respectively). These results stand in contrast to the statements 'I am full of appreciation seeing what applications AI technology can have', 'The use of AI technology improves efficiency of farm's production', and 'Most AI technologies have features assigned to them', for which the scores were clearly higher. This may indicate that farmers generally see the benefits

Table 3. The average value of indications regarding the statements on attitude towards AI technologies among farm owners from Poland, Romania, and Lithuania

Component	The statement	Poland	Romania	Lithuania
Cognitive (Behavioural beliefs)	Most AI technologies have features assigned to them.	5.45	5.20	5.10
	The use of AI technologies improves efficiency of farm's production.	5.15	4.65	4.50
Emotional (Normative beliefs and subjective norms)	I am full of appreciation seeing what applications AI technologies can have.	5.25	4.35	4.10
	I would have confidence in using AI technology.	4,45	3.65	3.25
Behavioural (Behaviour)	I would not have a problem with implementing AI technology in my work.	3.55	3.20	3.05

Note: response scale from 1 to 6, where 1: totally disagree, 6: totally agree

Source: own performance based on interview data

of implementing artificial intelligence solutions in the agricultural sector (even if they are not exactly familiar with these tools), as long as it does not affect their farm. In such a situation, they are cautious in adopting modern technology or do not see such a need. The answers obtained may also suggest that lack of knowledge may not be the only barrier to the use of AI among small farms, but that there are other obstacles that prevent them from adopting innovations. These weaknesses were identified in the next step of the analysis.

Farmers were first asked the question: 'What new technologies do you use in your daily work? Are they based on AI?' When it came to answering this question, the surveyed farmers from the three countries were unanimous. All of them (100% of responses) stated that they did not use new technologies based on artificial intelligence in their work. Some of them used GPS navigation, computer software, or Excel spreadsheets, but they did not consider these tools as AI.

Further results indicated that the lack of use of artificial intelligence is typical for small-scale farms. When asked 'Does anyone close to you use new technology', farmers could not give an example of such use among family, friends, or acquaintances who owned small-scale farms. However, there were examples for large-scale farms (6 indications) and agricultural companies (9 indications) in terms of: fertilising the field, sowing or ploughing, taking digital measurements (e.g. using drones), and automation of animal feeding. This demonstrates that the implementation of artificial intelligence in the agricultural sector is clearly differentiated by farm area and scale of production. This was one of the most important barriers mentioned by the interviewed owners of small-scale farms. The interviewees also pointed the high cost of implementing this type of solution. However, when asked about the price of these tools, most of them could not indicate a price, nor did they know the technical details about specific installations. Some of the interviewees also claimed that they did not see the need to use AI due to their low scale of production, and also due to their attachment to traditional agricultural production methods. At the same time, the small share of positive answers to the question about plans to use AI in the future (20% of farms in Poland and 15% in Romania and Lithuania) aligns with the relatively low ratings for the statement 'I would not have a problem with implementing AI technology in my work'. The list of barriers to AI application in the opinion of farm owners is shown in Table 4.

5. Discussion

The results presented above are worth contrasting with the conclusions of other works. First, it must be said that AI technologies are increasingly being used in business to support decision-making processes; to perform simulations and forecasting; and as a basis for building competitive advantages and increasing the efficiency of business processes, services, or product satisfaction. Departments of businesses

Table 4. The most important barriers to the use of artificial intelligence among small farms in Poland, Romania, and Lithuania

Poland	Romania	Lithuania
– too small area of the farm (45%) – too small scale of production (50%) – too high price/cost of new technologies (30%) – lack of knowledge in this field (35%) – attachment to traditional production methods (15%) – use of artificial intelligence is risky (10%)	– too small area of the farm (35%) – too small scale of production (40%) – too high price/cost of new technologies (45%) – lack of knowledge in this field (50%) – attachment to traditional production methods (45%) – artificial intelligence will not replace humans (10%)	– too small area of the farm (35%) – too small scale of production (30%) – too high price/cost of new technologies (40%) – lack of knowledge in this respect (40%) – attachment to traditional production methods (25%) – using AI is ineffective (15%)

Source: own performance based on interview data

where such solutions are used include marketing, research and development, production, and quality management (Buntak et al., 2021). AI techniques are being used in several sectors which are seeing the fastest growth in the recent years, such as finance, healthcare, retail, pharmaceutical research, intelligent process automation, and marketing (Ayed & Hanana, 2021). These areas can be supplemented by industries such as the high-tech industry, automotive and assembly, telecom, travel, transport and logistics, electric power and natural gas, and engineering. Of the aforementioned, the leading sectors in AI use are financial services, automotive, high-tech and telecommunications, where around 30% of companies have adopted one or more AI technologies (Eager et al., 2020). Artificial intelligence-based methods are also widely used in research fields related to climate change, environmental monitoring, food safety, and food security (Galaz et al., 2021).

Many studies point to the benefits of AI in the agricultural sector (e.g. Eli-Chukwu & Ogwugwam, 2019; Panpatte, 2018; Patel et al., 2021). However, it seems that the main stakeholders so far are large corporations: agricultural machinery manufacturers and the processing industry. The use of AI by agricultural producers is most common on large-scale farms. For instance, Panpatte (2018) cites an example from India, where the Microsoft Corporation is working with 175 farmers in the state of Andhra Pradesh, providing services and solutions for land preparation, sowing, and adding fertiliser and other crop nutrients. On average, a 30% increase in crop yield per ha has already been witnessed in comparison to the previous harvests. Companies such as BASF, Monsanto, Bayer, Pioneer, and John Deere are using the data retrieved from farms to provide tailored insights and recommendations to farmers with the assistance of AI technologies (Ryan, 2022). But, in the words of Javid et al. (2022), 'the future of AI in agriculture will require a significant focus on universal access because the majority of cutting-edge technology is only utilised on big, well-connected farms'.

For this reason, there are only few publications on the application of AI by small farms. First, the low level of AI use in the small-scale agriculture is a common phenomenon worldwide. The Deep Knowledge Group (2019) report indicates that in no CEE country does AI technology distribution in agriculture exceed 3%. Secondly, the level of involvement of modern technologies in small farms is particularly low, due to the marginalization of these entities, digital exclusion (poor Internet penetration), low levels of technical knowledge, and the capital required. The inability to take advantage of AI benefits will increase the gap between small farms and commercial farms (Mehrabi et al., 2021; Wolfert et al., 2017; Hennessy et al., 2016). It is emphasized that the latter, with their higher investment capacity and ability to generate marginal productivity gains over larger areas, will be the main beneficiaries of innovative technologies (Tzachor et al., 2022). Therefore, in order to increase the use of artificial intelligence in small-scale farms, it is advisable to launch a system of grants and advisory assistance that will increase awareness amongst farmers and make these technologies more accessible (Gwagwa et al., 2021; Tessler et al., 2019). Without these mechanisms, agribusiness corporations are poised to make large gains at the expense of smaller farms, to the detriment of rural sustainability.

6. Conclusions

This paper points out that the implementation of artificial intelligence by farms can increase the level of sustainability of the agricultural sector, mainly in an environmental context, which supports the fulfilment of the 'green economy' strategy of the European Union. At the same time, the role of small-scale farms in this strategy is emphasised, as they are entities with a higher level of sustainability, due to more traditional methods of food production, a relatively high level of self-consumption, or lower chemicalisation of production due to lack of capital. However, compared to commercial agribusinesses, small-scale farms are characterised by an unfavourable income disparity. In this case, the implementation of AI can contribute to the improvement of economic performance and reduce disparities between small and large actors in the agricultural market. The conducted research proves that the level of use of modern technology in small farms, even those with a high sustainability index, is, in practice, zero. Thus, the titular question can be answered: small sustainable farms in Poland, Romania and Lithuania do not display technological smarts. This fact reveals the necessity of dedicating artificial intelligence-based solutions to small farms. This is especially true for countries with a high share of smallholder agriculture and a fragmented agrarian structure, as the low scale of production and land area, in addition to high acquisition costs, are considered to be the main barriers to the application of AI. Therefore, instruments for subsidising the purchase of technology are recommended; in the case of EU countries, these may be targeted funds under the second pillar of the Common Agricultural Policy. The barrier of the too-small scale of production and lack of capital can also be reduced by developing systems of cooperation in the purchase and use of innovative machinery and equipment (e.g. creating and disseminating a model for a technology co-ownership agreement). It is also postulated that rural areas should be covered by broadband Internet and that farmers should be guaranteed access to powerful computers connected to the Cloud and data storage. Last but not least, it is crucial to organise (e.g. at the headquarters of agricultural advisory centres, chambers of agriculture, or village halls) a series of training courses on the application of artificial intelligence in agriculture, with particular emphasis on small farms. This process should involve representatives of companies producing the technology, IT specialists, scientists, social partners and, finally, farmers using such solutions.

The authors realize that the results of this research should be confirmed due to the limited sample size. In these conditions, our inferences are appropriate for small-scale farms from three countries – Poland, Romania and Lithuania. Generalizing the results to other countries requires additional research and comparisons of the results of the analyses. This study can therefore be regarded as a prelude to further research. Future work should also include farms that have implemented AI solutions. It will be particularly important to find examples of small and medium-sized entities that have done so, and to answer the question of the motivators that led them to implement innovations. This sort of research will also make it possible to assess how economically and environmentally effective the application of AI is on this level of farm. Finally, in view of the implementation of the new CAP rural development plans from 2023 onwards, it will be important to identify selected methods to support this process within EU countries. An opportunity to launch new research will be a new scientific project carried out in 2023-2025 by the authors of this publication.

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