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Research article

Determinants of the Internet of Things adoption by millennial farmers

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Abstract: Indonesia is experiencing difficulties in ensuring the sustainability of the agricultural system as the younger generation experiences reluctance to enter the business of agriculture. Smart farming is believed to be a solution to the difficulty of millennials entering the business of agriculture. One of the main elements of smart farming is the Internet of Things (IoT). This study aims to determine the factors that encourage millennial farmers in Central Java to adopt IoT-based innovations using a behavioral reasoning theory (BRT) perspective. Data were collected from 120 millennial farmers in Central Java; we applied BRT, an analytical technique, to examine IoT adoption by millennial farmers. Primary survey data analysis was carried out by applying structural equation modeling techniques. The results showed that millennial farmers accepting the adoption of IoT technology is a factor of relative advantage and social influence. Meanwhile, the reason for rejecting the adoption of IoT technology is technology anxiety. This research provides information on the reasons for accepting and reasons for rejecting the adoption of IoT in agriculture by millennial farmers in Central Java province, which will be helpful for the government in the design of a program to attract millennials to go into business in agriculture.

Keywords: IoT adoption; millennial farmer; PLS-SEM; behavioral reasoning theory; Indonesia

1. Introduction

The results of the Indonesian Population Census in 2020 revealed that the total population of the millennial category in Indonesia was 25.87% (69,901,000 people) of the total population of 270.2 million people, meaning that the potential productive workforce is large in number [1]. However, Indonesia's agricultural condition is relatively poor in terms of sustainability. This is because, in recent years, very few young people have been interested in working in agriculture. The perception of work in "dirty" and "inferior" agriculture causes the younger generation to have low interest in working in agriculture [2]. On the other hand, the imports of various agricultural products (horticultural and processed) are increasing and threatening domestic agricultural products [3]. Agricultural development in Indonesia is still very dependent on conventional technology (labor-intensive) and natural resources [2].

The slow adoption of information technology and innovation has led to the low productivity and competitiveness of Indonesian agricultural products. In contrast, agricultural production systems in developed countries have adopted agriculture 4.0, known as smart farming. The output of smart farming systems is high productivity, competitiveness and cleanliness [4]. For this reason, the foundation of agriculture in Indonesia must begin to adopt information technology (agriculture 4.0).

The government of Indonesia's policy must be directed to encourage the acceleration and transformation of information technology-based innovation. This should be done to increase the attractiveness of the agricultural sector for the younger generation (millennial/digital generation) and provide incentives and convenience for millennial farmers to practice in the agricultural sector to encourage increased productivity, added value and competitiveness [3–6]. Thus, Indonesian agriculture needs to change so that it does not export raw materials anymore but exports finished products based on the power of innovation [3].

To realize this hope, the Ministry of Agriculture Republic Indonesia introduced the term millennial farmer. The term millennial farmer is believed to be able to attract the younger generation to work in agriculture. The term millennial farmer is momentum because the millennial generation will dominate in the next few years in the labor structure in Indonesia [3]. The Ministry of Agriculture of the Republic of Indonesia gave rise to the terminology of millennial farmers to maintain the sustainability of the Indonesian agricultural system and accelerate the adoption of information technology in agriculture. The basis for the involvement of the younger generation (millennial farmers) is that the agricultural sector requires human resources to have the following characteristics: (1) digital technology skills (digital farmers), (2) on-farm activities that are supported by technologies, (3) a product processing regime (agro-industry) that is already based on digital technology and (4) efficient marketing through the utilization of digital information/technology. In Indonesia, millennial farmers are defined as farmers aged 19–39 years or with a millennial spirit who are adaptive to digital technology, so they are not rigid in identifying and verifying technology [4].

One-third of farmers in Central Java province are millennial farmers. The presence of millennial farmers in agriculture is expected to create innovation and improve quality, productivity, and competitiveness. Head of the Central Java Agriculture and Plantation Service, Suryo Banendro, said the number of millennial farmers in Central Java Province was 975,600 people (33.7%) from 2.88 million farmers in Central Java. A total of 57,600 people are undergraduates whose presence is believed to increase agricultural products' competitiveness.

For this reason, fundamental changes must be made to catch up with the agricultural sector. The use of information technology and the innovation movement are the keys to building the agricultural sector in the future. Currently, the synergy between the advantages of information technology and the power of innovation is accommodated in smart agriculture. Smart agriculture is an agricultural management concept based on information and communication technology [6–12] well as innovation, which entails utilizing agricultural machinery and equipment (agricultural tools and devices) and digital technology in agriculture to increase productivity, added value, competitiveness and benefits in a sustainable manner [7]. In short, smart agriculture should be the basis of Indonesia's agricultural strength in terms of its presence in regional and global markets, thus attracting young people (millennials) to develop their business careers in agriculture [8]. One of the important components of smart agriculture implementation is the Internet of Things (IoT) [9,10]. IoT is a technology that farmers must apply when running smart agriculture. Because information technology has become a daily necessity for millennial farmers, millennial farmers must be maximized to increase the productivity, product quality, competitiveness and efficiency of agricultural production in Indonesia [12]. IoT is very effective in helping weather engineering that suits the needs of plants, because IoT can be built to automate crop cultivation through intelligent control for proper and efficient water use [12].

IoT assists farmers in obtaining information related to crop production success, including meteorological data and data on soil conditions, land use and market demand [5]. IoT technology also assists farmers in making informed decisions regarding the quantity and quality of agricultural products, and the efficient use of resources to obtain higher profits [3–6,12]. With IoT, agricultural productivity can be increased while minimizing the environmental impact [14]. Because of IoT's significant role in realizing this, it is called a solution for realizing smart agriculture [7,13,15].

Tren's innovation to win the competition in the market has shifted to a model of collaboration with other parties [16]. The paradigm of entrepreneurship has also changed, where winning the competition can not only result in meeting the customers' needs, but also be determined by how much creativity is possessed. Collaboration with other farmers, the government, academia and the community must be carried out to support the success of millennial farming businesses [12].

To realize these expectations, it is necessary to know the baseline of millennial farmers. Identifying the ability of millennial farmers to build networks by using IoT-based technology is very important. This requires knowing the factors that influence it. Based on this background, this study aims to determine the factors that encourage millennial farmers in Central Java to adopt IoT-based innovations. The derivation of this will be formulated as a strategy for utilizing IoT technology for millennial farmers in Central Java province.

2. Materials and methods

2.1. Basic methods of research

The basic method of this study is the comparative causal method [17–19], which is a study that aims to conclude the presence or absence of cause-effect relationships between the variables studied independent and dependent variables). From these variables, the aim is to determine the extent of influence of the independent variables on the dependent variables. The location of the study was chosen purposively as Central Java Province in consideration of this region's potential for agriculture because of the number of millennial farmers, i.e., as many as 975,600 people, or 33.7% of the 2.88 million farmers in Central Java [20]. The population in the study constituted ambassadors of millennial farmers in the province of Central Java. Interviews, observations and recordings were carried out for data collection. The research data consist of primary data and secondary data. The primary data consist of the business characteristics of millennial farmers, a business network map of the mastery of innovations applied by millennial farmers, the networking ability of millennial farmers and factors that influence the intention to adopt IoT-based innovations. All of these data were collected through interview and observation techniques. Meanwhile, the secondary data, which covers the agricultural potential of Central Java, monographs and other supporting data, were obtained through interviews and recordings.

2.2. Sample determination

Sample determination using purposive sampling is a sample determination technique carried out intentionally by considering specific criteria [21–23]. The sample criteria in this study were millennial farmer ambassadors domiciled in the province of Central Java, aged 19–39 years, running a business in agriculture (food agriculture, horticulture, animal husbandry and/or plantations), and who have been working on their business for at least two years. The total sample was 120 millennial farmers, as determined by considering the number of variables relative to the sample size (1:20) [24]. The total population of millennial farmer ambassadors in Central Java Province, as according to the Decree of the Minister of Agriculture of the Republic of Indonesia No. 434/KPTS/SM020/M/8/2021, was 189 people at the time of data collection. The selection stage of the millennial farmer ambassador sample began with the determination of 10 regencies that have the most millennial farmer ambassadors. Each regency was selected as an example of a millennial farmer ambassador by paying attention to the variety of millennial farmer ambassador businesses in the chosen regency. Thus, the number of samples in the study was 63.5% of the total population. The distribution of regency and the number of millennial farmer ambassadors selected as samples can be seen in Table 1.

Table 1. Distribution of the number of respondents by regency/city.

Number	Regency/Cities	Number (of people)
1.	Magelang	51
2.	Semarang	20
3.	Temanggung	13
4.	Sukoharjo	7
5.	Banyumas	5
6.	Purbalingga	6
7.	Wonosobo	3
8.	Purworejo	5
9.	Tegal	5
10.	Klaten	5
Sum		120

Source: Primary Data Analysis, 2022.

2.3. Data analysis methods

There are three model tests that utilize partial least squares (PLS) methodology: 1) Measurement model tests with test stages: measurement of reliability and validity of the construct; 2) Structural model tests to estimate the value of the coefficient of determination (R^2) and predictive relevance (Q^2); 3) Using bootstrapping functions to test the hypothesis to estimate the path coefficient that identifies the strength of the relationship between independent latent variables against latent dependent variables.

2.4. Testing measurement models (outer model)

The measurement model was evaluated with convergent validity, discriminant validity and reliability [25]. The data are valid if the loading factor value is > 0.60 and the average variance extracted (AVE) value is > 0.50. If the value of the cross-loading indicator on the variable is higher than for the other variables, the variable used is valid. If the composite reliability value is > 0.60 and the value of Cronbach's alpha is > 0.70, then the data used are reliable [26,27].

2.5. Structural model testing (inner model)

Structural models are evaluated by looking at the values of the coefficients of determination (R^2) and predictive relevance (Q^2). The R-squared value is used to assess the influence of independent latent variables on latent dependent variables. The criteria for the value (R^2) is > 0.67, which indicates that the model is good, and > 0.33 is moderate and > 0.19 is weak. The next structural model evaluation is the measurenent of how well the model produces the observation value, as well as the estimation of its parameters using the Q^2 value; if (Q^2) > 0, then the model has predictive relevance, but if the value is less than 0, then the model lacks predictive relevance [28].

2.6. Hypothesis testing

A PLS-based hypothesis test was carried out by using bootstrapping [29,30]. This study used a significance level of 5%, a t-statistical value of 1.96 and a p-value smaller than 0.05. If t-statistics ≥ t-table and p-value ≤ alpha (α), then Ha is accepted; H0 is rejected.

3. Results

3.1. Outer model evaluation

3.1.1. Reliability test

The reliability of an instrument in the outer model can be seen from the composite reliability and Cronbach's alpha values. Composite reliability and Cronbach's alpha are statistical techniques used to measure internal consistency in instrument reliability tests [25]. A variable is reliable when it has a composite reliability value and Cronbach's alpha above 0.7. The results of composite reliability and Cronbach's alpha output in this study are as follows.

Table 2. Composite value reliability and Cronbach's alpha.

Variable	Cronbach Alpha	Composite Reliability	Information
Openness to Change	0.745	0.852	Reliable
Social Influence	0.791	0.876	Reliable
Relative Advantages	0.852	0.899	Reliable
Technology Anxiety	0.892	0.933	Reliable
Risk Perception	0.704	0.871	Reliable
IoT Adoption Intention	0.873	0.914	Reliable

Source: Primary Data Analysis, 2022.

Table 2 shows that each variable meets the model assessment criteria, as each variable had a Cronbach's alpha value above 0.7, meaning that each variable had a high average internal consistency [31]. The composite reliability value was found to be above 0.7, indicating that the reliability of all variables is high. This suggests that all the variables in the study are reliable.

3.1.2. Discriminant validity

Proof of validity of discriminants means that two concepts differ conceptually and differences are demonstrable. Discriminant validity ensures that each variable differs from the other variables. Validity testing is carried out to determine how precisely a model/measuring instrument performs its measurement function [32]. Discriminant validity can be good if cross-loading tests show higher indicator values for each construct than for the other constructs [28]. The indicator's value is assessed based on the correlation between the item/component score and the construct score calculated via PLS. The individual reflexive size is considered high if the loading factor is > 0.70 for the construct you want to measure. Table 2 shows that each indicator is a strong predictor for each of the described variables. This is evidenced by the loading factor value of each indicator being greater than 0.7. Table 3 shows the values of loading factor indicators against the constructs in the study.

Table 3. Discriminant validity test results.

	Technology Anxiety (TA)	Openness to Change (OC)	Relative Advantages (RA)	IoT Adoption Intention (AI)	Social Influence (SI)	Risk Perception (RP)
RA 1	−0.355	0.243	0.844	0.344	0.477	−0.217
RA 2	−0.332	0.256	0.847	0.502	0.587	−0.239
RA 3	−0.337	0.318	0.835	0.568	0.575	−0.288
RA 4	−0.386	0.320	0.796	0.444	0.450	−0.233
TA 2	0.880	−0.379	−0.340	−0.404	−0.299	0.325
TA 3	0.922	−0.383	−0.428	−0.455	−0.392	0.319
TA 4	0.918	−0.364	−0.380	−0.443	−0.378	0.445
OC 1	−0.373	0.827	0.304	0.386	0.265	−0.202
OC 2	−0.234	0.753	0.192	0.214	0.235	−0.055
OC3	−0.374	0.852	0.325	0.247	0.147	−0.165
AI 1	−0.479	0.283	0.486	0.860	0.407	−0.221
AI 2	−0.321	0.354	0.540	0.908	0.423	−0.222
AI 3	−0.429	0.318	0.457	0.898	0.376	−0.131
AI 5	−0.399	0.267	0.472	0.737	0.356	−0.372
RP 2	0.427	−0.194	−0.296	−0.247	−0.224	0.896
RP 3	0.265	−0.128	−0.223	−0.242	−0.114	0.859
SI 2	−0.132	0.077	0.293	0.111	0.822	0.093
SI 3	−0.288	0.268	0.559	0.475	0.843	−0.268
SI 4	−0.353	0.176	0.504	0.413	0.832	−0.049

Source: Results of analysis processed with Smarta PLS 3.0, 2018.

Table 3 shows that the correlations of the RA construct with its indicators are higher than those with the other constructs. This is also true for the TA, OC, AI, RP and SI constructs with their respective indicators. This shows that each indicator in the research variable has greater cross-loading with itself than with other variable indicators. Therefore, it can be concluded that the indicators used in the study have met the condition for good discriminant validity in the preparation of each variable.

The next validity test uses each latent variable's AVE value parameter. The discriminant validity of the measurement model is said to be reflexive if the AVE value is greater than 0.5 [33]. Table 4 shows the AVE values corresponding to the validity test results.

Table 4. AVE values.

Variable	AVE	Information
Openness to Change	0.658	Valid
Social Influence	0.702	Valid
Relative Advantages	0.690	Valid
Technology Anxiety	0.822	Valid
Risk Perception	0.771	Valid
IoT Adoption Intention	0.729	Valid

Source: Primary Data Analysis 2022.

Based on Table 4, all variables in this study are suggested to be valid because they have an AVE value greater than 0.5. This shows that all variables can explain the diversity of all of their indicators [24,33,34].

3.2. Evaluation of the inner model (structural model)

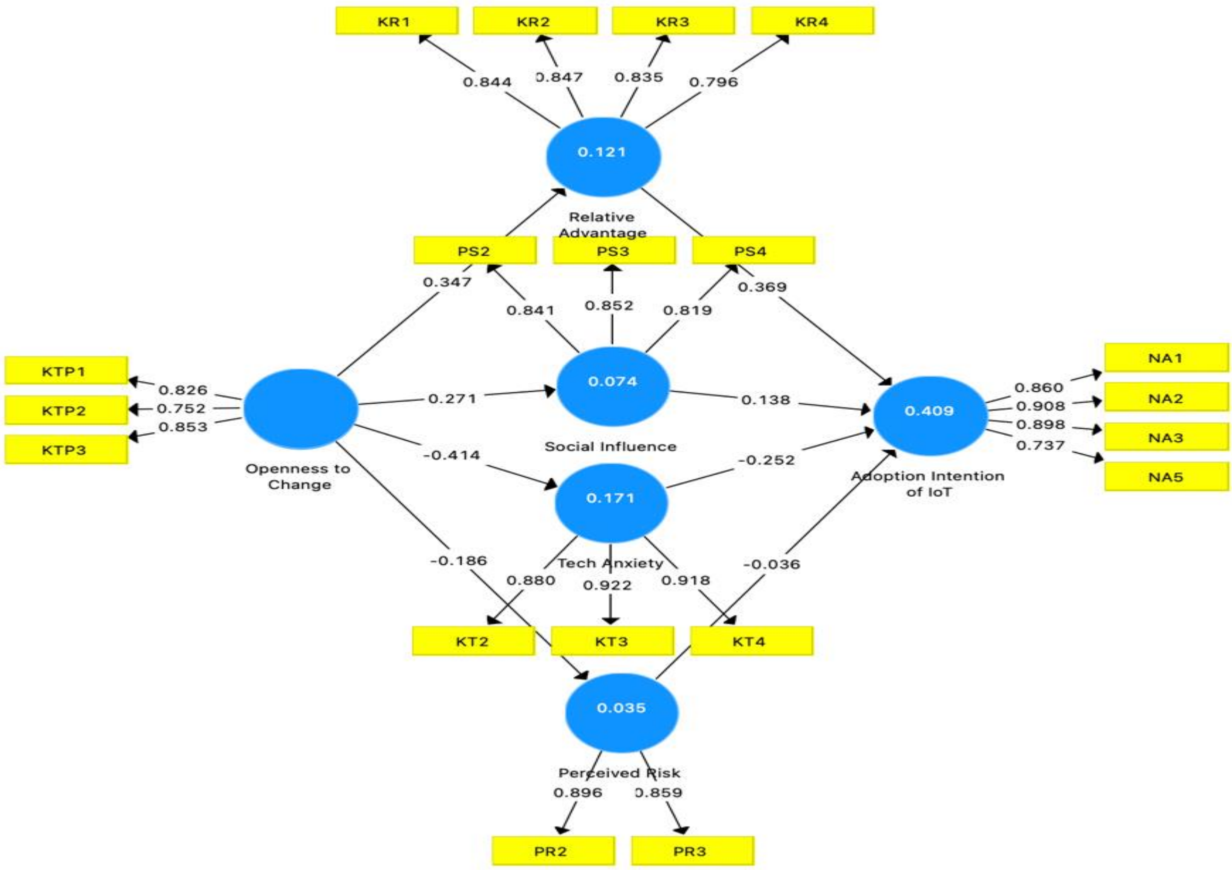

Figure 1. Research model.

Assessing the model (Figure 1) with PLS begins by looking at the R-squared value for each latent dependent variable. Changes in R-squared values can be used to assess the influence of certain independent latent variables on latent dependent variables. The value of the coefficient of determination is between 0 and 1. The coefficient of determination value was divided into three categories: 0.67, 0.33 and 0.19, indicating the strong, moderate and weak models [31,35]. Table 5 describes the R-squared and Q-squared values in the study results, All Q-squared values > 0, so it can be concluded that the model has predictive relevance values [30,36]. The following formula can calculate the value of Q-squared:

$$Q^2 = 1 – [\ 1 − (R^2 \text{ adjusted})^2] \quad (1)$$

Table 5. R^2 and Q^2 values.

Variable	R^2	Q^2	Information
IoT Adoption Intention	0.404	0.383	Weak; has predictive relevance
Relative Advantages	0.121	0.113	Weak; has predictive relevance
Social Influence	0.069	0.061	Weak; has predictive relevance
Risk Perception	0.035	0.026	Weak; has predictive relevance
Technology Anxiety	0.172	0.165	Weak; has predictive relevance

Source: Primary Data Analysis 2022.

The value of R^2 indicates that the independent latent variable's ability to predict the latent dependent variable is weak because the value of R^2 is below 0.5. Meanwhile, based on the resulting observation value, the Q^2 value shows that the latent variable in the study has sufficient predictive relevance because $Q^2 > 0$ [19,36].

3.3. Hypothesis testing (bootstrapping)

Table 6. Hypothesis test results.

Hypothesis	T-statistic	P-values	Notes
Openness to Change —› Relative Advantages	4.012	0.000	S
Openness to Change —› Social Influence	2.061	0.040	S
Openness to Change —› Perceived Risk	2.759	0.006	S
Openness to Change —› Technological Anxiety	5.815	0.000	S
Relative Advantages —› Adoption Intention of IoT	2.019	0.044	S
Perceived Risk —› Adoption Intention of IoT	0.880	0.379	NS
Social Influence —› Adoption Intention of IoT	1.970	0.049	S
Technological Anxiety —›Adoption Intention of IoT	3.556	0.000	S

Source: Primary Data Analysis 2022; S = Significant; NS = Non-Significant.

The structural model describing the interrelationships among the constructs is known based on its path coefficient, which assesses its significance level (T-statistic and p-value) with the bootstrapping procedure [58]. The structure of the model was tested by using a significance rate of 5%, i.e., a p-value smaller than 0.05. The proposed research hypothesis is declared acceptable if the p-value is less than or equal to alpha (α). Meanwhile, if the p-value is more than alpha (α), then the proposed research hypothesis is declared rejected. The results of hypothesis testing with bootstrapping procedures are presented in Table 6.

4. Discussion

4.1. Effect of openness to change on relative advantages

Based on the results of data analysis in this study, openness to change has a positive effect on relative advantages (0,347), so the hypothesis was accepted. This is indicated by a p-value of 0.000. These findings align with the findings in [30], which indicated that openness to change affects the adoption of IoT due to considerations of relative advantages. Thus, millennial farmers being more open to change in general, and the development of IoT in particular, means that more farmers will feel that IoT can provide added value and enable better and more effective performance in terms of managing their farming business. Farmers who are open to new methods, innovations and technologies can judge that IoT delivers better results. Millennial farmers in Central Java are open to innovations because they consider them beneficial in reducing work barriers, increasing competitiveness, improving performance and consumer satisfaction [34,59] and increasing profits [40].

4.2. Effect of openness to change on social influence

Based on the analysis in this study, information was obtained that openness to change positively affects social influence (0,271) with a p-value of 0.040, so the hypothesis was accepted. Openness to innovation makes farmers more receptive to the suggestions, inputs and ideas of others, which then becomes the impetus to adopt IoT. This finding aligns with those of [30], which indicates that the value of openness to change reinforces the reason for adopting IoT. Farmers who are open to other people's information regarding new methods, innovations or technologies will consider input from others (fellow farmers, associations or related government staff). Many millennial farmers in Central Java have joined various organizations or associations, including the Indonesian Organic Alliance, the Central Java Seed Breeding Association (HIPMAI), Indonesian Veterinary Paramedics and Inseminators (PRAVETINDO), the Indonesian Orchid Association and the Geographical Indication Protection Society. Being open to the surrounding environment is a key trait in millennials [41], so the adoption of IoT, which is believed to have a positive impact on productivity, quality, efficiency and profit [25, 26], is acceptable to millennial farmers

4.3. Effect of openness to change on perceived risk

Openness to changes negatively affects perceived risk (−0.186), as evidenced by a p-value of 0.006, so the hypothesis was accepted. This means that, if farmers are more open to change, then farmers will be more aware of the risks of adopting IoT. In other words, the risk perception of using IoT technology is low. This aligns with research that open-mindedness will reduce the reason for refusing IoT adoption [30]. When farmers feel that an innovation (IoT) brings benefits to themselves personally, the risk of adopting this will decrease. Millennial farmers' understanding of the impact of risk leads to adoption by millennials; this behavior was also observed for customers using m-banking in India [42]. Understanding the risks of adopting IoT is used as a consideration to reduce the risk of millennial farmers in adopting IoT [15].

4.4. Effect of openness to change on technological anxiety

Openness to change significantly negatively affects technological anxiety (−0.414), as indicated by a p-value of 0.000, so the hypothesis was accepted. A person's openness to change does not always positively affect the adoption of a technology/innovation. The existence of new technology/innovation makes millennial farmers anxious because farmers are not necessarily able to learn and then use it. This follows the research findings that openness to change influences farmers to reject new technologies/innovations [30]. Millennial farmers in Central Java are open to information (IoT technology). However, not all IoT technologies are adopted because they are worried about failing and negatively impacting their farming business performance. Farmers tend only to use IoT technology that is considered easy to use and profitable [8,22,26]. The technology used so far is only social media, which enables communication with business partners.

4.5. Effect of relative advantages on the IoT adoption intention

The analysis showed that relative advantages positively affect the IoT adoption intention (0.369) with a p-value of 0.044, so the hypothesis was accepted. This indicates that relative advantages affect the intention of IoT adoption. This means that the greater the perceived benefits of IoT, the greater the desire to adopt IoT. These findings align with previous research results [35,43], which indicate that relative advantages constitute one of the determining factors influencing a person's choice to adopt an innovation. Millennial farmers in Central Java province realize that IoT is beneficial and essential for improving the performance of their farming businesses. IoT simplifies work, improves efficiency and effectiveness, and provides better results than conventional agriculture systems [25,44].

4.6. Effect of social influence on the IoT adoption intention

The social lives of millennial farmers are very positively influential on their decision to adopt IoT technology (0.138). This study's results align with previous findings [8,30,38,43], which also indicate that adoption intentions are driven by the social influence where a person resides. This is indicated by a p-value of 0.049. This social influence comes from fellow millennial farmers, the people closest to them, communities or association members and the people considered important to farmers, who are usually used as references to ask for solutions or opinions about the farming business. Direct experience from fellow farmers, group input or officers' directions can encourage farmers to adopt an innovation [16].

4.7. Effect of perceived risk on IoT adoption intention

The results of the analysis produced information that perceived risk has an insignificant negative effect (−0.036) on the intention of IoT adoption, as indicated by a p-value of 0.379, so the hypothesis was accepted. This finding contradicts those in [45], which states that perceived risk affects the intention to adopt an innovation. In the context of this study, the small amount of risk from using IoT technology does not affect the intention of millennial farmers to adopt IoT technology. These findings indicate that millennial farmers have dared to take risks in terms of utilizing IoT technology. Farmers' risks include misuse of their data, data given to other parties without permission, and unilateral decision-making because it utilizes farmer data. Farmers do not feel risks when using IoT. This is possible because millennial farmers do not understand the risks of IoT as related to their data in detail. Besides that, they also look more at the benefits obtained when using IoT technology [10,44,46].

4.8. Effect of technological anxiety on IoT adoption intention

Technology anxiety negatively impacts IoT adoption intentions (−0.252). This is evidenced by a p-value of 0.000. These findings align with [47], which suggests that technological anxiety affects individuals' intentions to adopt innovations. The higher the anxiety about the presence of technology, the lower the level of IoT adoption by millennial farmers. Anxiety in this study included fear of failing to use IoT, excessive worry about using IoT, and anxiety because they were not used to it. This anxiety occurs because farmers do not fully understand IoT's benefits. Generally, the IoT technologies that millennial farmers have adopted tend to only be in the form of e-commerce to support the marketing of their products [19]. Even then, it is just a platform that the general public widely uses. Few millennial farmers have adopted IoT to support production or cultivation activities [47]. Technological anxiety is a barrier to IoT adoption because the image of IoT in traditional agricultural societies is perceived as complex and challenging [30].

Kecemasan teknologi berdampak negatif pada niat adopsi IoT (−0,252). Ini dibuktikan dengan p-value sebesar 0,000. Temuan ini sejalan dengan [47], yang menunjukkan bahwa kecemasan teknologi memengaruhi niat individu untuk mengadopsi inovasi. Semakin tinggi kecemasan hadirnya teknologi, maka semakin rendah tingkat adopsi IoT yang dilakukan petani milenial.

5. Conclusions

Openness to change affects several factors related to millennial farmers' intention to adopt IoT: their reasons for adoption (relative advantages and social influence) and reasons against it (perceived risk and technological anxiety). Meanwhile, relative advantages, social influence, and technological anxiety influence the intention to adopt IoT. This article contributes as another overview of IoT adoption by millennial farmers. The indications of this study are as follows: increasing the intention of millennial farmers to adopt IoT technology can be achieved by providing education related to the benefits or advantages of adopting IoT technology, optimizing the role of associations, communities, and/or groups to motivate farmers to adopt IoT and providing IoT-based innovation training to reduce farmers' anxiety or concern about IoT technology and instead make IoT-based technology a part that will help millennial farmers to increase efficiency, productivity, and profits.

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Conflict of interest

The authors declare no conflict of interest.

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