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FACTORS AFFECTING THE ADOPTION OF AGRICULTURAL AUTOMATION USING DAVIS'S ACCEPTANCE MODEL (CASE STUDY: ARDABIL)

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Taking into account that traditional agricultural methods reduce the farm performance and make agriculture economically ineffective, development of intelligent machinery is essential for improving the quality of crops and agricultural activities. The most important issue in development of agricultural technologies lies in users' willingness to adopt it. Therefore, the purpose of this study is to investigate the key factors of Davis's model in automation acceptance in agriculture. Presented paper describes an applied research with a survey approach through a questionnaire. Questionnaire data were collected from 378 people and respondents include university students, farmers and experts in a randomized sampling from the Ministry of Agriculture. Firstly, the questionnaire data were described in a form of statistical numerical characteristics. Secondly, in order to verify the data normality, the Kolmogorov-Smirnov test was calculated in SPSS and the relationship between the variables was investigated in the conceptual model. Subsequently, hypotheses were tested via appropriate statistical models using LISREL and SPSS software. The results showed that for all hypotheses, the *T*-test exceeds 1.96 and the significance level is less than 0.05. In such a manner, all hypotheses were confirmed at 95% level, and the path coefficients in the hypotheses H1, H2 and H6 were negative – indicating the negative effect of the independent variable on the dependent variable in the hypothesis. In the other hypotheses, these were positive – indicating the positive effect of the independent variable on dependent variable. By means of modelling, it was found that there was an inverse relationship between social and individual factors with perceived usefulness, as well as an inverse relationship between social factors with perceived ease-of-use, while there was a positive and significant relationship between other factors. According to a set of fitting indices, the research conceptual model was appropriate and Cronbach's coefficients for each factor were greater than 0.7, suggesting that the questionnaire was valid. On the basis of findings, the better a person understands the usefulness of automation, the more likely this person is to adopt it. Since the risk and issues related to it play an important role in farmers' decision making, it is recommended that future studies address the issue of risk in adopting precision farming technology.

Keywords: attitude; intention to use; LISREL; perceived usefulness

In Iran, agriculture is the largest economic sector after services, accounting for approx. 20% of gross national product and the major share of non-oil exports. Moreover, a large number of people is employed in agriculture; therefore, the sector growth largely determines the economic growth of the country (Ebrahimi et al., 2017).

According to the World Food and Agriculture Organization (FAO), the world's population is expected to reach 9.1 billion by 2050. Therefore, to feed this population, food production should increase by at least 70% and developing countries must double their food supply. Since this is not achievable by traditional agricultural methods, it is necessary to modernise the technologies in the agricultural sector (Sreekantha, 2016; Beloev, 2016). It is typical for developed economies that high technologies and innovative solutions associated with the progressing economy globalisation, as well as wider access to outlets play a vital role in their growth (Biały and Žarnovský, 2017).

One of the solutions that can mitigate or eliminate the damage caused by traditional agriculture is its automation; the lack of this technology is one of the most significant issues in the agricultural sector (Masoudi, 2016). The automation is in fact a software permanent management focused on all system processes (day-to-day), which is monitored and controlled by a central processor unit (Goodarzi and Sadeghi Fard, 2014). Machine automation allows these systems to perform their work efficiently, reliably, accurately and almost without any human intervention (Schueller, 2006) and automation utilization benefits in agriculture include increases in export and production, production quality improvement, time saving, production cost reduction, reduction of issues related to water losses in the agricultural system, boom in agriculture, conservation of biological resources, and decrease in the growth of urban migration.

Diversification of agricultural systems around the world makes it difficult to use automation and control. Many outdoor agricultural automation systems that may be exposed to a wide range of environmental and atmospheric conditions, such as high temperature, humidity, etc. cannot perform accurate automation. Considering the developing countries, one particular concern is associated to the lack of workforce due to automation, as well as the lack

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of willingness to adopt the automation in a region due to the economic, social, cultural, technical and environmental conditions.

Due to population growth and rising costs in the coming years and demand for food, there should be strategies for higher production and less waste. Utilization of robots can be justified with higher production, waste reduction and reduction of current costs by means of more and more accurate monitoring (Torabi et al., 2014).

The first step in the development of agricultural automation is to identify consumer behaviour and factors affecting its acceptance. Therefore, this research was conducted with the aim of identifying the factors affecting the agricultural automation adoption in Ardabil and providing a model for automation acceptance in the agricultural sector. In this study, consumer behaviour was assessed on the bases of behavioural models – the most common conceptual models.

Development of hypotheses and conceptual model

1. Individual factors

There are multiple individual factors significantly affecting the consumer behaviour (Amen, 2010). In research, human capital measurements have been based on assessment of data on education, age, gender, and family size of the farmer (Keelan et al., 2014). The education level of a farmer increases their ability to understand presented ease aspects and usefulness of a new technology (Okunlola et al., 2011; Adebiyi and Ekonola, 2010). Studies on the adoption of microcomputers in agriculture (Putler and Zilberman, 1988), crop reduction and precision agriculture (Roberts et al., 2004) show a positive relationship between habitat and acceptance. Age is also one of the factors influencing the new technology acceptance. Older people have gained knowledge and experience over time and are more able to evaluate technical information in contrast to young farmers (Mignouna et al., 2011; Kariyasa and Dewi, 2011).

H1: Individual factors affect the perceived usefulness of the automation application in agriculture.

H2: Individual factors affect the perceived ease aspects of automation application in agriculture.

2 Social factors

Social norms represent one of the subcategories of social factors that affect technology adoption with an effect on attitude of the individual towards an object (Malte et al., 2008; Chong et al., 2010; Verma and Sinha, 2018).

H3: Social factors affect the perceived usefulness of the automation application in agriculture.

H4: Social factors affect the perceived ease aspects of the automation application in agriculture.

3. Organizational factors

Access to support services is also recognized as a key aspect of technology acceptance. Farmers are often informed on the existence and benefits of new technology via expanding agents. Many authors have reported a positive relationship between post-sales services and automation adoption (Bonabana-Wabbi, 2002; Sserunkuuma, 2005; Akudugu et al., 2012).

H5: Organizational factors affect the perceived usefulness of the automation application in agriculture.

H6: Organizational factors affect the perceived ease aspects of the automation application in agriculture.

4. Automation features

Tests that can be performed at a small scale before the full automation adoption represent another significant factor influencing the automation acceptance (Doss, 2003; Mignouna et al., 2011). These are necessary to introduce any new technology to farmers, so they can evaluate and understand suitability of tested technology under their own conditions (Karugia et al., 2004).

H7: Automation features affect the perceived usefulness of the automation application in agriculture.

H8: Automation features affect the perceived ease aspects of the automation application in agriculture.

5. Perceived usefulness (PU)

In regard to the numerous variables affecting the system utilization, perceived usefulness is considered a prerequisite for automation acceptance and behavioural intent (Kim et al., 2007; Callum et al., 2014; Park and Chen, 2007; Mansour et al., 2017; Shirmohammadi, 2004; Lotfi and Bakhsayeshi, 2010; Wafaei, 2009; Davis, 1989).

H9: Perceived usefulness affects the attitude towards the agricultural automation.

H10: Perceived usefulness affects the willingness to use the agricultural automation.

6. Perceived ease of use (PEOU)

Perceived ease of use is a degree to which every individual believes that particular system utilization will facilitate his work (Davis, 1989; Verkantesh et al., 2003). According to Venkatesh and Davis (2000); Liu et al. (2009); Saghafi et al. (2017), a positive relationship was found between PEOU and PU.

H11: Perceived ease of use affects the attitude towards the agricultural automation.

H12: Perceived ease of use affects the willingness to use agricultural automation.

7. Attitude (ATU)

Attitude can be expressed as one's view of the chosen act (Yadav and Pathak, 2016). Attitudes have a significant effect on the individual's behaviour, and this relationship becomes more intense when it is related to one's health.

H13: The attitude towards automation affects the intention to use the automation in agriculture.

8. Intention to use (IU)

The intention to use (IU) is a key factor for the actual use (Davis et al., 1989). In terms of the technology utilization, a decision to willingly use the technology in full extent is generally positive (Turner et al., 2010).

H14: The intention to use the automation affects the actual (AU) automation utilization in agriculture.

Based on aforementioned hypotheses, conceptual research model can be presented as follows:

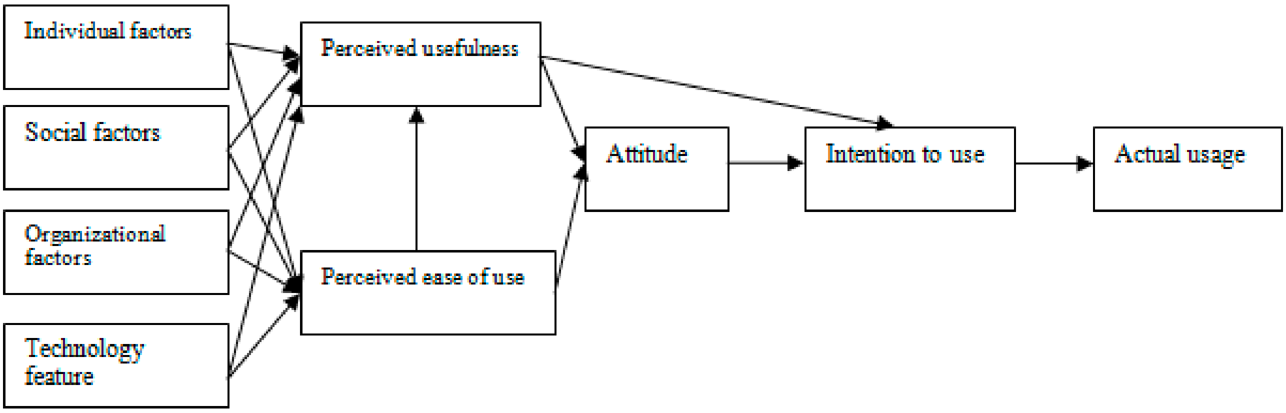

Fig. 1 Conceptual framework for research (source: author's research)

Material and methods

The purpose of this study was to investigate the factors affecting the automation adoption in agriculture in Ardabil. The statistical population of this research consisted of three academic circles, experts from the Ministry of Agriculture (Jahad) and farmers, 27,670 people in total. Randomized sampling method was used. On the basis of sample size set by Krejcie and Morgan (1970) and the Cochran formula utilization, 380 individuals were calculated as sample size:

$$n=\frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left[\frac{z^2pq}{d^2}-1\right]}=\frac{\frac{1.96^2\times0.5\times0.5}{0.5^2}}{1+\frac{1}{27{,}670}\left[\frac{1.96^2\times0.5\times0.5}{0.5^2}-1\right]}=380 \quad (1)$$

where:

- n – sample size
- N – size of statistical population
- z – acceptable random error
- P – ratio of success
- q – failure ratio
- d – degree of accuracy

Considering the possibility that the questionnaires might not be filled out by all respondents, the questionnaires were distributed to 385 respondents. Finally, after deleting the invalid questionnaires, 378 questionnaires remained to be observed; therefore, study sample size was 378 individuals, indicating the response rate of 98.18%. Data collection was performed using library and field methods. The questionnaire was developed by the researcher based on Davis's model (Fig. 1). It consists of several main sections; the first to seventh sections are: organizational factors, individual factors, perceived usefulness, perceived ease of use, attitude, intention to use and actual usage. Using Bartlett test and confirmatory factor analysis, a number of questions was deleted in each section in order to lower the factor loading, and a final questionnaire with 80 questions was developed.

Factor analysis and Cronbach's alpha coefficient were used to determine the questionnaire validity and its reliability:

$$r_a=\frac{j}{j-1}\left(1-\frac{\sum_{j=1}^{n}s_j^2}{s^2}\right) \quad (2)$$

where:

- j – number of questionnaire items
- s_j^2 – variance of the subtest j
- s^2 – variance of entire questionnaire or test

The data normalization assumption was performed by means of Kolmogorov-Smirnov test (K-S). Confirmatory factor analysis examines the relationship of items or questions with the structures; this process was carried out using the LISREL software. The *T*-test statistic is used to determine the significance of the relationship between the variables. Since the significance is checked at a level of 0.05, if the observed factor loading shows a *t*-value of less than 1.96, it is not significant.

Chi-squared test (X^2) was used to measure the correspondence between the experimental and theoretical curves. This test indicates the designed model is based on actual data. Finally, to test the research hypotheses, structural equation modelling was employed, which is a strong multivariate analysis technique from the family of multivariable regression.

Results and discussion

Evaluation of data normality and questionnaire validity and reliability

In order to verify the data normality, Kolmogorov-Smirnov test was calculated for the variables of individual, social and organizational

Table 1 Demographic characteristics of the respondents

Characteristic	Number of respondents	Level	Absolute frequency	Relative abundance
Gender	378	man	321	84.9
		woman	57	15.1
Age	378	less than 20 years old	7	1.8
		21–29 years old	148	39.2
		30–39 years old	111	29.4
		40–49 years old	87	23
		50–59 years old	23	6.1
		over 60 years old	2	0.5
Level of education	378	illiterate	61	16.1
		diploma and lower	85	22.5
		B.A/B.S	111	29.4
		M.A/M.S	81	21.4
		PhD and higher	40	10.6
Average monthly income	378	less than 1 million	144	38.2
		between 1 and 3 million	157	41.5
		between 3 and 5 million	36	9.5
		more than 5 million	41	10.8
Employment status	378	graduate student	94	24.9
		academic staff	37	9.8
		agricultural expert	75	19.8
		farmer	172	45.5
Experience of agricultural work	378	less than 5 years	92	24.3
		5 to 14 years old	155	41
		15 to 24 years old	105	27.8
		25 to 34 years old	19	5
		35 to 49 years old	7	1.9

factors, technology characteristics, perceived usefulness, perceived ease, attitude, intention to use and actual use by means of SPSS software (Table 2).

Based on the data shown in Table 2, the significance level for all components exceeds value 0.05, indicating that these variables have a normal distribution, and structural equations can be used to test the hypotheses in terms of parametric testing.

Confirmatory factor analysis results for each variable conducted via the LISREL software are presented in Table 4 for each variable separately. It should be emphasized that, in order to reduce the number of variables, the factor loading obtained should not exceed value 0.3 (Momeni and Qiyomi, 2017). However, before performing the factor analysis, the point that needed to be addressed first was to make sure that the number of data for the factor analysis is appropriate. For this purpose, Kaiser-Meyer-Olkin (KMO) index and Bartlett test were used (Table 3).

According to Table 3, the KMO index is 0.843, which is in the range above 0.6. Therefore, the research sample size is appropriate for factor analysis. Furthermore, the significance level of Bartlett test is less than 0.05, suggesting that the factor analysis is suitable for identifying the structure (factor model).

Therefore, a confirmatory factor analysis could be used to analyse the questionnaire. The *T*-test was used to test the significance of relationships between variables. Since the significance is checked at a level of 0.05, if the factor loading observed shows a *t*-value lower than 1.96, it is not significant. Each question with a factor loading less than 0.3 was deleted from the questionnaire.

Estimation of research conceptual model

Research model test was carried out using the structural equation modelling method (Figs. 2 and 3).
The hypotheses test results are summarized in Table 4.

Table 2 Kolmogorov-Smirnov test before and after normalization

Variable	Kolmogorov-Smirnov test before normalization		
	Statistics	Degrees of freedom	Significance level
Individual factors	4.05	378	0.000
Social factors	3.87	378	0.000
Organizational factors	3.11	378	0.000
Technology features	2.32	378	0.000
Perceived usefulness	4.87	378	0.000
Perceived ease of use	3.24	378	0.000
Attitude	5.62	378	0.000
Intention to use	3.36	378	0.000
Actual usage	4.52	378	0.000
Variable	**Kolmogorov-Smirnov test after normalization**		
	Statistics	**Degrees of freedom**	**Significance level**
Individual factors	0.11	378	0.09
Social factors	0.16	378	0.22
Organizational factors	0.07	378	0.45
Technology features	0.16	378	0.14
Perceived usefulness	0.17	378	0.13
Perceived ease of use	0.19	378	0.12
Attitude	0.20	378	0.12
Intention to use	0.13	378	0.11
Actual usage	0.12	378	0.15

Table 3 Bartlett test and KMO index for evaluated data

KMO index		0.843
Bartlett test	Chi-squared test	465.93
	Degree of freedom	1225
	The significance level	0.000

Table 4 Hypotheses test results

Hypothesis	Independent variable	Dependent variable	Path coefficient	T statistics
H1	individual factors	perceived usefulness	-0.41	-5.28
H2	social factors	perceived usefulness	-0.32	-4.38
H3	organizational factors	perceived usefulness	0.36	4.52
H4	technology features	perceived usefulness	0.34	4.45
H5	individual factors	perceived ease of use	0.92	13.55
H6	social factors	perceived ease of use	-0.43	-5.46
H7	organizational factors	perceived ease of use	0.62	11.20
H8	technology features	perceived ease of use	0.65	12.10
H9	perceived ease of use	perceived usefulness	0.52	8.80
H10	perceived usefulness	attitude	0.74	13.09
H11	perceived ease of use	attitude	0.41	5.30
H12	perceived usefulness	intention to use	0.97	14.44
H13	attitude	intention to use	0.50	8.72
H14	intention to use	actual usage	0.95	13.90

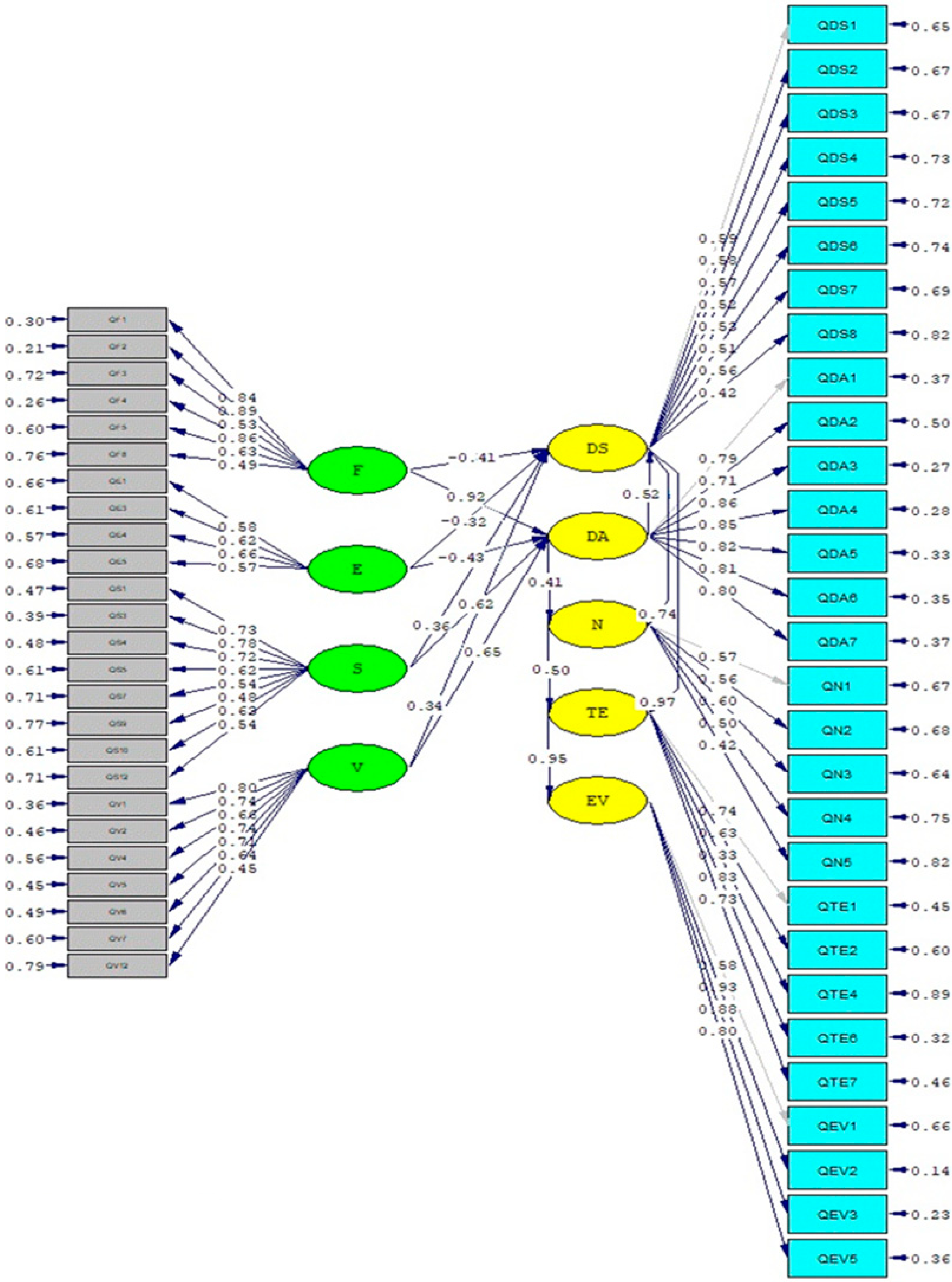

Fig. 2 Estimation of standard correlation coefficient in model
Chi-square = 3,735.17; *df* = 1,357; *P*-value = 0.00000; RMSEA = 0.068

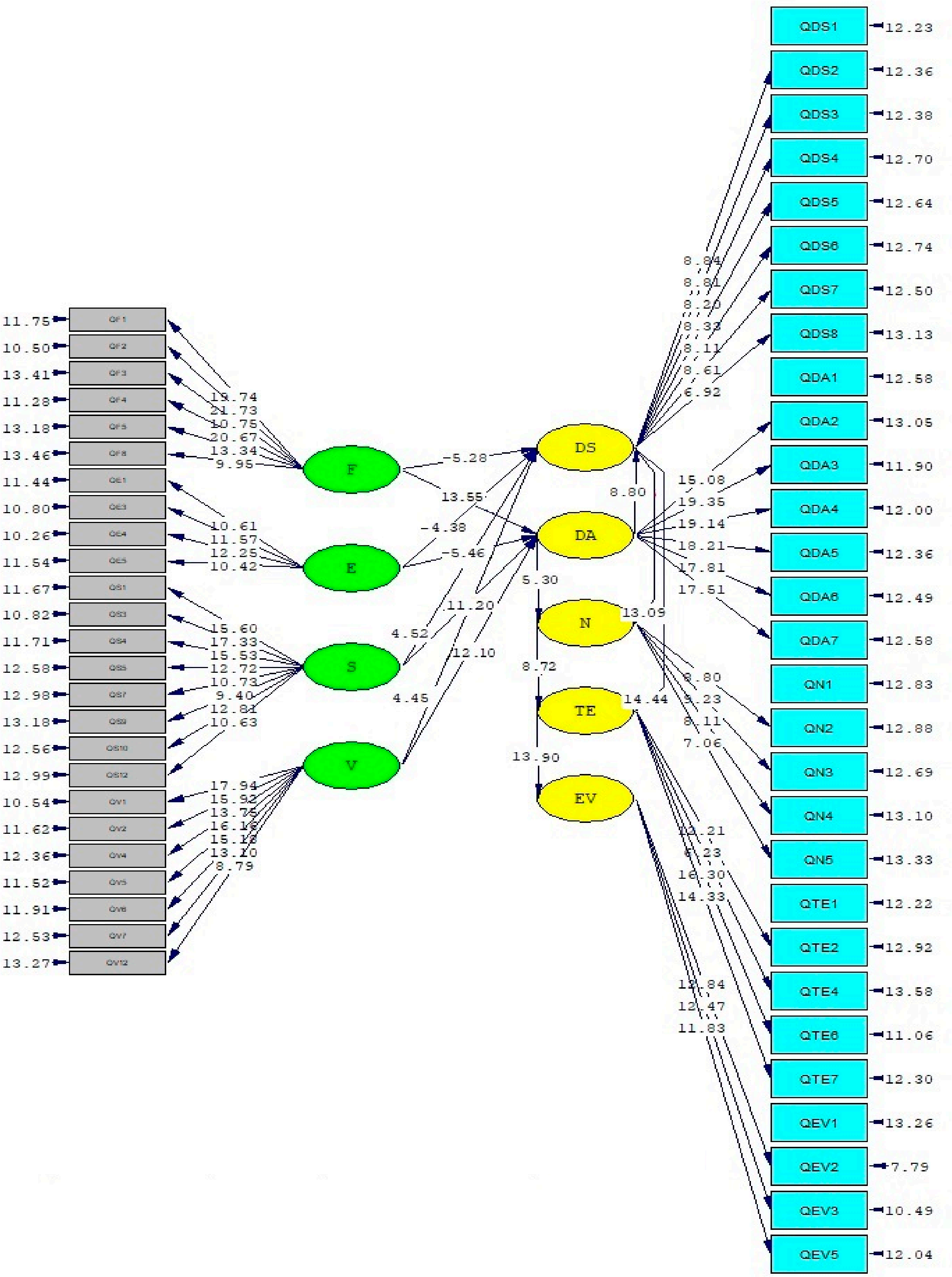

Fig. 3 Estimation of the t-statistic in the model
Chi-square = 3,735.17; *df* = 1,357; *P*-value = 0.00000; RMSEA = 0.068

Table 5 Model suitability indices

	Model fit indices	Acceptable range	The amount earned
Chi-square	Chi-square	–	3,735.17
Degree of freedom	*df*	–	1,357
The ratio of chi-square to the degree of freedom	x^2/df	3>	2.75
The root mean estimation of the approximation error variance	RMSEA	0.1>	0.060
The root mean square of the remainder	RMR	0.1>	0.060
Goodness of fit index	GFI	0.9<	0.954
Non-normalized fitting index	NNFI	0.9<	0.962
Comparative fitting index	CFI	0.9<	0.987

The results shown in Table 4 indicate that for all hypotheses, the *t*-test exceeds the value of 1.96 and the significance level is lower than 0.05. Therefore, all hypotheses were confirmed at 95% level, and the path coefficients in the hypotheses H1, H2 and H6 were negative, suggesting the negative effect of the independent variable on the dependent variable in the hypotheses. The other hypotheses are also positive, indicating the positive effect of the independent variable on dependent variable.

Structural equation modelling and significance indices

In general, to determine the fit of the estimated model, various indicators are used and the model fitness must be reasoned by more than one. Therefore, these indicators should be combined. The values of model fit indices are shown in Table 5.

According to Table 5, all model fit indices are acceptable. Therefore, on the basis of fitting indices, it can be concluded that the conceptual research model is appropriate and calculation results for relationships in the research model are valid and reliable.

Conclusion

Using the structural equation modelling results, it was determined that there is a significant relationship between individual factors and perceived usefulness. The correlation coefficient between the two variables was negative, indicating that with an increase in individual factors, the perceived usefulness decreases. This means that experience; prior knowledge; self-confidence; financial status; education level; land area; and the number of family labourers do not have positive impact on the productivity increasing. The reason for this was poor and unfavourable classes in knowledge creation.

There was observed a significant relationship between social factors and perceived usefulness. The correlation coefficient between the two variables was negative, indicating that with an increase in social factors, perceived usefulness decreases. This means that social factors, such as mental norm; trust in friends; and classes, played a significant and positive role in farmers' understanding of technology usefulness. Therefore, these classes should be presented in a more specialized and practical way.

There was also a significant relationship between organizational factors and perceived usefulness. The correlation coefficient between the two variables was positive, suggesting that with an increase in the organizational factors, there is an increase in the perceived usefulness and vice versa. In general, this means that membership in the rural cooperative; advertising; behaviour of the host companies; sponsor organization availability; support services; justification training; low interest loans; long-term repayment deadlines; and timely funding can effectively provide new technology utilization.

The positive correlation coefficient between automation and perceived usefulness means that the automation features, such as relative advantages; compatibility; low complexity; visibility; testability; no need for further labour; optional adoption, can make the technology more useful.

The positive correlation coefficient between individual factors and perceived ease means that farmers' experience, knowledge and confidence; education level and good financial status make it easier to use the automation.

There was also a significant relationship between the automation features and perceived ease. The correlation coefficient between the two variables was positive, suggesting that with an increase in automation features, there is an increase in perceived ease. Therefore, it seems that relative advantages; compatibility; low complexity; the lower need for workforce; optional adoption; low start-up costs; etc. make it easier to understand the ease of use of technology.

There was a significant relationship between perceived usefulness and attitude. The correlation coefficient between the two variables was positive and indicated that with an increase in perceived usefulness, the attitude increases. In other words, the more people understand the benefits of automation, the better their attitude toward using it. These findings are consistent with the results presented by Siregar et al. (2017).

A significant relationship between perceived usefulness and the intention to use the automation was also observed. The correlation coefficient between the two variables was positive, indicating that with an increase in perceived usefulness, the intention to use also increases. In other words, when farmers consider the automation utilization to be useful, they tend to use it more.

A significant relationship between attitude and intention to use was also shown. The correlation coefficient between the two variables was positive and indicated that with an increase in attitude, the intention to use is also increased.

There was observed a significant relationship between the intent to use the technology and its actual usage. The correlation coefficient between the two variables was positive, indicating that with an increase in the intent to use the technology, its actual usage increases. This means that, when using automation, the person will actually use it in agriculture.

In general, based on the model fit indices obtained in the research, it seems that Davis's technology acceptance model is suitable for investigating effective factors in agricultural automation in Ardabil.

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