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A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT)

Mohammad Hossein Ronaghi [a,*], Amir Forouharfar [b]

[a] Department of Management, Shiraz University, Shiraz, Iran
[b] Department of Public Administration, University of Sistan and Baluchestan, Zahedan, Iran

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ABSTRACT

Smart Farming is the application of modern technologies, tools and gadgets for increasing the agricultural crops quality and quantity. The Internet of Things (IoT) technology has had a prominent role in the establishment of smart farming. However, the application of this technology could be hard and, in some cases, challenging for the Middle Eastern users. Therefore, the research purpose is to identify the influential factors in the adoption and then application of IoT in smart farming by farmers with a contextualized approach in Iran, a typical Middle Eastern country. Thus, the Unified Theory of Acceptance and Use of Technology (UTAUT) has contextually been used as the theoretical model of the research. The results accentuated and proved the positive impacts of performance expectancy (H1), effort expectancy (H2), social influence (H3), individual factors (H4), and facilitating conditions (H5), on the intention to use IoT technology. Ultimately, the results were indicating the significant impact of behavioral intention on the actual usage of IoT technology (H6). One of the implications of the research is for the IT policymakers in the agricultural sector in the Middle East, where water and cultivable land are two valuable but scarce economic resources. Hence, smart farming could not be promoted unless the farmers had fulfilled its prerequisite factors proposed by the research results for using the IoT technology.

1. Introduction

Agriculture had always been a major strategic activity for supplying food. In 2018, more than 821,000,000 people were suffering malnutrition worldwide and each year more than 10,000,000 people die of starvation [1]. Moreover, agriculture, especially in developing countries, has usually faced with the prevailing challenges of food security, food safety, sustainable development and health. In the early and mid-twentieth century, the applied techniques for confronting these challenges were non-digital. Although industrial agriculture was developed to be responsive to the food challenges of the era, besides the consumers' fad for keeping a healthy life style, it had its own endogenous challenges of low resource efficiency, climatic changes, and animal exploitation [2]. However, exogenously agriculture industrialization developed plenty of agricultural businesses worldwide. The application of IoT technology especially in the twenty first century not only revolutionized smart industrial agriculture but also dramatically affected tourism, medicine, transportation, commerce, etc. One of the major effects of the IoT was its optimization effect in using natural and economic resources [3]. The increasing trend in using the IoT is going to connect approximately 50 billion things to the Internet up to the end of the current year (2019) [4]. The IoT user-friendly capabilities have remarkably altered the potential usages of the Internet. The first stage in using the IoT is the technology adoption. Once the users adopt the technology then it could develop and optimize the decision-making processes [5], as well as the controlling measures, which lead to more productivity and sustainability [6,7].

On the other hand, most technological issues show their technological robustness or conversely their impotency on the ground and within practical contexts. Concerning the current study, most recently new and innovative researches were being done on IoT within the agricultural sector. For example, Hamad et al. [8] have lately studied the impact of smart phones on the access of the farmers to new agricultural information and knowledge. The result of the interview with 230 farmers in their research revealed that most of the farmers were using their smart phones for improving and evaluating the condition of their farmlands.

* Corresponding author.
E-mail addresses: mh_ronaghi@shirazu.ac.ir (M.H. Ronaghi), amir.forouharfar@gmail.com (A. Forouharfar).

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Another recent research by Bu and Wang [1] investigated the impact of agricultural IoT on deep learning. Moreover, Verdouw et al. [2] have already presented an architectural framework based on IoT for food and agriculture systems. Their research credibility and validity has been verified by the EU. The Verdouw et al.'s [2] framework could tremendously contribute to the future accurate modeling and architecture of IoT-based systems. Another relevant example is Khanna and Kaur's [9] study. They comprehensively studied the IoT academic endeavors for acquiring precision agriculture (PA). They analyzed the degree of each influential researcher's as well as each university's contribution to the PA literature via IoT studies. Additionally, Hsu et al. [10] have presented a platform for the application of IoT in agriculture based on computer clouds. The Hsu et al.'s [10] presented platform, which is based on the introduced cloud, not only made the collecting and analyzing of great bulks of data possible, but also facilitated the applicability of efficient communications between the farms and the information resources. Nevertheless, even a superficial study of the literature on The Middle East smart farming reveals that smart farming is still a neglected and under-theorized issue in this region where water as a requisite of any agricultural activity is so precious a commodity, which could push the countries in the region toward war. Without doubt, adoption of appropriate smart technologies and then their customization with the need of the technology users could tremendously benefit the states of the region not only in optimal usage of their water resources but also in driving agriculture toward more productivity and profitability. Hence, the research question is:

What technological factors could affect the intention to use IoT technology by the farmers in the Middle East region?

2. Literature review

2.1. Internet of Things

Everything could be incorporated into the domain of IoT with the usage of sensors in the Internet networks. The Internet is institutionalized in daily and business lives of modern people [11]. IoT is using service-oriented architecture (SOA) based on IP with the intention to make integrity between its entities and also to make interaction plausible among those entities [9]. Fig. 1 has illustrated multiple usages of IoT based on the interactions between the things and human.

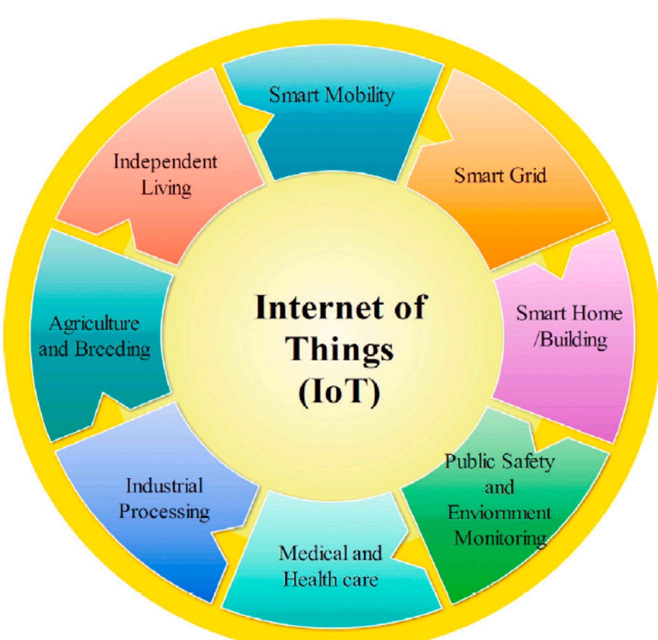

Fig. 1. Various usages of IoT [9].

Among numerous functions of IoT, 'Industry 4.0' is a new layer of this technology, which is going to monopolize most organizational activities [12]. The functions of 'Industry 4.0' are collecting, analyzing, storing and controlling the activities in real time, which have led to the dramatic decrease of production costs and the outstanding increase of service and goods quality. The concept of 'Industry 4.0' is directly related to the installation of smart equipment and instruments for optimal controlling of resources, as well as increasing efficiency besides improving flexibility. On the other hand, once the data from the sensors, machines and different instruments of an industry were collected and controlled within an Internet framework then it is Industrial Internet of Things (IIoT) which was introduced for the first time in 2012 by General Electric Digital Corporation. Development of IIoT besides Industry 4.0 have made the long-distance usage of robotic regulator systems for the timely supervisory and controlling measures in businesses and industries applicable [13]. In addition, one of the significant usages of this modern technology is in agriculture, which could lead to quantum leap forward.

2.2. IoT in the agricultural industry

Besides other positive effects, improvement of technology has strikingly affected agricultural crops [4]. Agricultural crops are environmentally dependent commodities. For example, environmental conditions such as climate and pests are seriously affecting the crops [2]. Thus, environmental monitoring and- if it would be possible- controlling are two major obsessions of the farmers everywhere in the world. IoT have contributed technophile farmers in abating these daily and persistent obsessions. For example, framers could diagnose some information such as soil temperature [14], soil moisture [15] and plant diseases [16] by using sensors which are accompanied by the Internet networks. IoT in the agricultural domain consist of various Internet-based techniques. Table 1 has summarized the main techniques of IoT in recent smart farming.

The use of IoT in farming has led to a great bulk of data and hence the

Table 1
IoT technologies in Smart farming [17].

IoT Technology	Application in Agriculture	Benefits in Agriculture
WSNs: Sensor nodes with radio communication Capabilities	Sensors integrated together to monitor various physical parameters	Easy collection and management of data gathered from sensors
Cloud Computing (on-demand computing): A type of Internet-based computing	Provides shared processing resources and data to computers and other devices on demand	Easy collection and management of data gathered from cloud computing services like agriculture fields maps, cloud storage, etc.
Big Data Analytics: The process of examining and analyzing large data sets	Access to various forms of data types	Uncover patterns, correlations, market trends, customer preferences, and other useful information
Embedded Systems: A computer system that consists of both hardware and software	System performs specific tasks, such as monitoring, controlling and efficient management of various activities	Productions costs can be reduced to a remarkable level which will increase profitability and sustainability
Communication Protocols: The backbone of IoT systems to enable connectivity	These protocols facilitate exchange of data over the network in various data exchange formats	Easy collection and management of tons of data gathered from sensors and cloud computing services, cloud storage, etc.

need to analyze and find the intricate data structures [18]. Table 2 has summarized some of the researches on the use of IoT in smart farming in the recent eight years.

Furthermore, in recent years, precision agricultural techniques were fundamentally affected by the Forth Industrial Revolution. This modern industrial revolution is the result of the data technology convergence with the artificial intelligence (AI). The Forth Industrial Revolution connects the cyber and physical technologies. According to Sung [27], "The Fourth Industrial Revolution will send a ripple effect of far-reaching repercussions throughout the labor-intensive field of agriculture." He believes:

Table 2
Summarization of some researches on the use of IoT in smart farming in the time span from 2013 to 2020.

References	Study Focuses	Results
[17]	Reviewing IoT and agricultural unmanned aerial vehicles (UAVs) in smart farming	They reviewed and systematically presented the main principles of IoT technology, consisting smart sensors, different types of IoT sensors, the networks and protocols that are being used in smart farming, as well as the IoT solutions for more efficient smart farming.
[1]	Proposing a smart farming IoT system based on deep reinforcement learning	They presented a four-tier IoT system via deep reinforcement learning which consists of the 1st tier or agriculture data collecting, the 2nd tier or edge computing, the 3rd tier for transmission, and the 4th tier or cloud computing.
[19]	Building an IoT infrastructure for agriculture education	Proposed a system that consisted open source software. The system was tested and then implemented according to the Gatton Campus website's data. Additionally, a dashboard was also designed for the end-user application.
[20]	Introducing an IoT online monitoring system based on cloud computing	An integrated framework consisting IoT, cloud computing and data mining technology in the modern agriculture was proposed via the IoT technologies' analyses in farming
[21]	Using IoT for just-in-time monitoring of agricultural crops logistics up to the delivery stage to the final consumers	Proposition of a real-time monitoring service based on industrial IoT to manage agrifood logistics
[22]	Using IoT-based e-commerce delivery	Using scenario analysis and interval number approaches in IoT-based e-commerce delivery for monitoring and assessing fruit freshness
[23]	Introducing IoT-based monitoring and forecasting via hybrid programming and parallel computing	Proposed an integrated service system for agricultural drought monitoring and forecasting as well as irrigation amount forecasting
[24]	Using wireless sensor network and data mining techniques for knowledge discovery and leaf spot dynamics of groundnut crops	Application of data mining techniques, besides wireless sensor network for discovery of new agricultural knowledge on the impact of environmental conditions on plant diseases.
[25]	Introducing a wireless sensor network for greenhouse climate control.	Introduction of a micro-climatic supervision and controlling system. The system collects and analyzes the data on climate, watering, pests, and fertility by wireless sensors.
[26]	Proposing an information service system of agricultural IoT	Proposed an information system for agricultural IoT based on distributed architecture (i.e. tracking the agricultural crop via distributed Internet servers of IoT).

Combining artificial intelligence and big data will evolve into a high-tech industry that operates itself. These technologies allow for precision agriculture, such as yield monitoring, diagnosing insect pests, measuring soil moisture, diagnosing harvest time, and monitoring crop health status. In particular, the Internet of things (IoT) will measure the temperature, humidity, and amount of sunlight in production farms, making it possible for remote control via mobile devices. It will not only boost the production of the farms but also add to their value.

The advent of the Fourth Industrial Revolution has also led to the brand new life-changing and industry forming disruptive technologies. The disruptive technologies have disseminated and consequently penetrated into traditional techniques of agriculture [28]. A few examples of these disruptive technologies, which are emerged in the agricultural domain, are Remote Sensing, Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Big Data Analytics (BDA) and Machine Learning (ML) [29]. IoT as one of the major disruptive technologies have been used in modern wireless networks. A recurring example of the IoT in agriculture is the usage of wireless sensor networks (WSN) in a farm. WSN usage affects the agriculture productivity, efficiency and effectiveness [21,30]. WSN have also made the soil quality, climatic, humidity, plant and animal biomass monitoring possible. Moreover, in the studied context of this paper (i.e. Iranian smart farming), the use of smart digital electricity meter and smart digital water meter are very frequent. The Iranian farmers use the meters to control the electricity and water consumptions in their farmlands. Another factor, which has dramatically contributed precision agriculture, is the use of unmanned aerial systems (UAS) in agriculture. This technology has provided low-cost environmental monitoring and scanning as well as photographing to the farmers. The UAS have paved the way for the accurate and high-resolution long distance photographing [31]. Hence, these days, the use of drones in agriculture is increasing. The drone usage in agriculture acts as a supporting system for the agricultural decisions [32]. Finally, numerous arrangements of these technological techniques and methods have successfully been incorporated into new technological configurations for smart farming in a wide arena from Europe, America and Australia [33,34], as well as, Brazil [35], India [36], and Italy [37], to Ireland [38].

On the other hand, there are numerous challenges in using IoT in the agricultural industry. For example, the instruments and apparatuses of IoT in the agricultural sector must be able to work in remote and mostly sever climatic conditions, e.g. under the hot sun or in the humid conditions of the greenhouses. Hence, these agricultural instruments of IoT besides being applicable in these severe conditions, must have the capability of functioning under Internet cut-offs or low speeds. Furthermore, agriculture is a time-consuming and seasonal activity and the consumers of agricultural products mostly expect healthy, organic and fresh products. Yet, multiple inevitable intermediaries between the producers and the final consumers have not only increased the price but also elongated the process and the time of delivery [2]. By applying smart agriculture, methods, and techniques via IoT, the farmers could increase their production, improve their diagnosis and add agility to their reaction. Thus, on one hand they will be empowered via IoT technologies to proactively prevent losses and on the other hand, to decrease the controlling and delivery time for their crops [39].

2.3. The selected model for technology acceptance and use in this research

Venkatesh et al. [40] presented their influntial model for the acceptance and use of technology after studying eight models of technology adoption within the information technology domain. The studied models which were incorporated into their final model are Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), the

Motivational Model (MM), Theory of Planned Behavior (TPB), the PC Utilization Model, Combined TAM and TPB (CTAM-TBP), Innovation Diffusion Theory and Social Cognitive Theory.

Additionally, after Venkatesh et al. [40] proposition of the Unified Theory of Acceptance and Use of Technology (UTAUT), many researchers (e.g. Hardy et al. [41]; Lescevica et al. [42]; Gharaibeh et al., [43]; Shiferaw and Mehari [44]) have tried to use the model in different technological contexts so far. The UTAUT model was not only tested within different geographical contexts but also it was contextualized within numerous technology acceptance fields which are ranging from mobile wallet [45], open government data [46] mobile health [47], mobile learning [48] to mobile banking [49], and mobile payment [50].

UTAUT presents substituting constructs in respect to Davis's model [51]. Since UTAUT model was used in different researches in various technological arenas, it was proved that it could be a suitable contextualization tool for measuring the success and adoption of information technologies [52–54].

Furthermore, before the current study in this paper, the UTAUT model has previously applied in various agricultural contexts. For example, Liang [55] has used the UTAUT model for assessing the acceptance of the last-mile technology (i.e. a telecommunication technology at the final section of a telecommunication network for carrying signals via the neighborhood infrastructure to the final home and business users, hence, last-mile) among the rural farmers of Chinese Guizhou province. The study results revealed the importance of environmental factors in the last-mile technology usage among the studied farmers. In another study of the UTAUT model within the agricultural context, Beza et al. [56] have applied the model for assessing the mobile SMS technology acceptance that was designed for collecting farmers' data in the smallholder farms. In this research, 125 Ethiopian farmers were participated. Additionally, Faridi et al. [57] in their study on 538 paddy farmers in Rasht County, Northern Iran, incorporated two models of UTAUT and initial trust model (ITM) to assess water and soil conservation measures (WSCM). The study results showed that effort expectancy (EE), in the context of the studied region in Iran, had the most significant impact on the farmers' attitude toward WSCM. Other researchers such as Li et al. [58] have applied a developed model of UTAUT. Li et al. [58] applied a developed version of the UTAUT for the acceptance of precision agriculture among 449 Chinese farmers in three provinces of China. The research results revealed that the "perception" of precision agriculture benefits among the studied farmers, in the context of China, the same as facilitating conditions' (FC) role, has a significant role in shaping the behavioral intention (BI).

Thus, by considering the high potential of the UTAUT model in predicting the intention to use new IT technologies as well as its frequency of application in the agricultural contexts, the researchers of the current paper decided to use UTAUT model in their study.

It is noteworthy to mention that in this model, the behavioral intention and usage of technology are assessed through four factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) [20]. Moreover, later individual factors (If) were also added to the developed model.

3. Methodology

3.1. Research context

Middle East and North Africa (MENA) usually share the same geographical and hence climatic conditions, which affect their agriculture. Water in both regions is one of the most valuable commodities that its severe scarcity in MENA could have crushing repercussions not only for the regional agriculture but also on the geopolitics of MENA. The studied country (Iran) share many characteristics of the countries in MENA. First, it is a vast populated state with approximately 84 million populations (except the Persian Gulf states with the populations lower than 4 millions, most of the MENA states are populated countries). Then, the MENA states are not usually the inventor or the producer of new technologies. Iran is not an exception. Therefore, because of their technological lag they are always and mostly consumers of the Western technology with few exceptions such as Iran which tries to substitute Chinese technology with the Western technology due to its imposed sanctions and its inevitability to access high-tech Western technologies. Furthermore, all MENA states share a semi-arid climate, which is predicated to be aggravated in the next decades and consequently could cause overwhelming shock in the countries' food security. For example, in case of the studied country (Iran), FAO has predicted declining trends for the agricultural products of the country. This specialized agency of the UN has also predicted that the wheat production growth of the country is going to decline from 2.01% in the years 2009–2018 to 1.39% in the interval 2019–2028 [59]. Moreover, the same agency has predicted a sharp drop in the wheat exportation capacities of Iran from 187 kt in the interval 2009–2018 to 30 kt in the year 2028 [59]. Could technology ameliorate the food security conditions in MENA? And especially in Iran? The answer by the authors of the paper is positive. Proper technology usage, especially low-cost available technologies such as IoT, could be one of the choices of the states' policymakers to absorb, relief, or avoid such a fatal and cataclysmic agricultural shock.

Considering the case of Iran, the historical role of agriculture, besides the exploitation of large oil and gas reservoirs in the 20th century have collectively formed an agro-petro economy in Iran. Currently, in the year 2020, the oil and gas industry of Iran is under unprecedented shattering sanctions. Although the oil and gas industrial sector still continues its shaky existence due to its shabby and outdated technologies, the only critical sector, which could save the country - with the assumption that the current condition continues for a long time - is its agriculture. The released data by FAO shows 17% of the population of Iran in 2017 was working in the agricultural sector and more than 28% of the lands of the country were dedicated to agriculture (Table 3). Moreover, in the same year the estimated GDP of Iran, derived from the agriculture sector was equal to 9.5% [60].

On the other hand, these days information technology (IT) has tremendously benefited the agricultural sector worldwide. The use of IT in agriculture or Precision Agriculture (PA) (e.g. around-the-clock use of instruments, special software and IT services for monitoring the soil quality or plant growth) is growing day in, day out. A contextualized approach to the study of the precision agricultural technologies in Iran revealed that among the four influential factors (social, environmental, economic and technological) for the acquisition of PA the technological factor had a significant and leading role, due to the transition of Iran's agriculture from a traditional agriculture to a modern agriculture [61]. Thus, the contextualized study of the usage of the IoT as one of the common techniques in PA and hence in smart farming within the studied country is justifiable.

Furthermore, this study could also contribute other MENA countries with the same technological ecosystems and climatic conditions to learn from the technological pros and cons of the implementation of IoT in a resembling country for the intention of acquiring a smart farming.

Contextualization of a model usage is like exposing a metal to the crucible of experience. Each new context could bring out a neglected or

Table 3
Iran's agricultural sector statistical information [60].

	year		
	1997	2007	2017
Forest land area (% of total land area)	5.7	6.6	6.6
Agricultural land area (% of total land area)	39.2	29.5	28.2
Food production value (2004-06 mill. I$)	17,214	27,072	26,447
Agriculture, value added (% GDP)	9.2	7.2	9.5
Food (excl. fish) exports (mill. USD)	659	2996	5526
Food (excl. fish) imports (mill. USD)	2889	4003	8354
Employment in agriculture (%)	23.6	22.8	17.6
Agric. value added per worker (constant USD)	6494	6975	10,209

rarely seen aspect of the model and hence could contribute to the model modification and ultimately its all-inclusiveness. Context is the inter-related conditions in which an entity exists, or it is exposed to, occurred or tested. The intention behind any contextualization is an endeavor to understand the dynamics of particular context [62].

3.2. Research method

After careful consideration of the IoT technology application literature on precision agriculture, the constructs of Beza et al.'s [56] questionnaire were considered to be incorporated into the researchers' questionnaire. The justification behind this selection was the agricultural context of the Beza et al.'s [56] questionnaire as well as its variable sufficiency, which was covering most of the significant reviewed variables on IoT in agriculture.

In the next step, the Beza et al.'s [56] questionnaire was modified according to some agricultural experts' views in the Iranian context to make it more compatible for a study on the IoT technology in Iranian agriculture.

For evaluating the research variables, a questionnaire with 27 questions was designed by the researchers. In this questionnaire (Appendix 1), four questions were demographical questions and the rest of the questions were covering the factors stated in the research hypotheses in the next section. Table 4 has elaborated on the variables in the research questionnaire.

As it was mentioned above, designed questionnaire of the research was modified in accordance with the received views from three university experts in the field. Therefore, the face validity of the research was adjusted according to the experts' views.

Moreover, for measuring the content validity, the content validity ratio (CVR) method was used. The CVR for each index was calculated. It is noteworthy that the CVR, within the significance level of 95%, should be more than 0.75 to be considered as a satisfactory content validity for an index [63]. The values of the ratio were statistically established. To test the reliability of the research questionnaire Cronbach's Alpha was used. The calculated values of Cronbach's Alpha were also presented in Table 5. Based on the presented values for Cronbach's Alpha in this table, it could be claimed that the reliability of the research measurement tool is statistically acceptable. Reliability is acceptable if Cronbach's alpha equals 0.7 or more [63]. The scales show good reliability with Cronbach's alphas >0.7.

To evaluate convergent validity, the average variance extracted (AVE) for each construct was evaluated against its correlation with the other constructs. AVE is the average amount of variance in indicator variables that a construct is managed to explain. Where AVE>0.5 and the CR (composite reliability) > 0.7, then convergent validity is confirmed [64]. The values of this index were shown in Table 5 and all the research AVEs have been confirmed.

Another validity measurement, discriminant validity examines the extent to which a latent variable is truly distinct from other latent variables in predicting the dependent variable [65]. One popular approach to assess discriminant validity, which was also implemented in the current research, was through examining the correlation matrix among constructs. The results which were presented in Table 6 indicate the acceptability of the research discriminant validity.

Table 4
Variables in the research questionnaire.

Variables	Definition
Performance Expectancy (PE)	Individuals' perception that technology usage will lead to the increase in performance.
Effort Expectancy (EE)	Individuals' perception of the ease of technology usage.
Social Influence (SI)	Individuals' perception in respect to the acceptance or non-acceptance of technology usage by others.
Individual Factors (IF)	Each individual's characteristics.
Facilitating Conditions (FC)	The extent that an individual believes that technical and organizational infrastructure could support the technology usage.
Behavioral Intention (BI)	The behavioral propensity of an individual for the voluntary adoption and usage of technology.
Use Behavior (UB)	The frequent usage of technology for different but relevant activities and tasks.

Table 5
Reliability and validity of the research model.

Variable	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	Convergent Validity
Performance Expectancy	0.864	0.871	0.649	established
Effort Expectancy	0.811	0.793	0.583	established
Social Influence	0.827	0.841	0.539	established
Facilitating Condition	0.793	0.822	0.613	established
Individual Factors	0.788	0.834	0.547	established
Behavioral Intention	0.853	0.895	0.625	established
Use Behavior	0.866	0.858	0.574	established

On the other hand, by considering the total number of 60,000 farmers in the studied region (Iran – Fars Province), 420 farmers were selected via the Krejcie and Morgan Table. The sampling method was convenience sampling. However, only 392 were willing to participate in the research. Furthermore, the research data were collected from the 2019 autumn to the 2020 winter (approximately within 110 days). Thus, the participation percentage is 93.3%. Finally, the path analysis was implemented via LISREL software for evaluating the research goodness-of-fit. Later for acquiring the normality test the researchers used SPSS software.

3.3. Research hypotheses

Performance expectancy (PE) is the degree that an individual thinks that technology usage could benefit him in reaching a better performance in his tasks [40]. PE is identified as one of the influential factors on the behavioral intention [44]; therefore, we can propose the following hypothesis:

H1. Performance expectancy has a positive influence on the intention to use IoT technology.

Effort expectancy (EE) is the perceived degree of convenience in using a system or a technology [40]. Many researches were suggested that EE affects the behavioral intention of using technology [66,67]. Thus, the second hypothesis could be stated as:

H2. Effort expectancy has a positive influence on the intention to use IoT technology.

Social influence (SI) indicates the degree of individual perception of the others' idea toward the usage of technology and system [40]. In some researches, it was demonstrated that there was a statistically significant relationship between SI and the behavioral intention [68,69]. Hence, the third hypothesis of the research is proposed in the following:

H3. Social influence has positive impact on the intention to use IoT technology.

In Venkatesh's model, individual factors (IF) were assumed as mediators. In this research, the authors assumed the individual factors as independent variables because of their significance and hence the fourth hypothesis studies the impact of the individual factors on the farmers' intention:

H4. Individual factors affect the intention to use IoT technology.

Table 6
Discriminant validity and correlations.

	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating condition	Individual Factors	Behavioral intention	Use Behavior
Performance Expectancy	0.842						
Effort Expectancy	0.342	0.867					
Social Influence	0.114	0.267	0.796				
Facilitating condition	0.247	0.185	0.256	0.812			
Individual Factors	0.267	0.411	−0.163	−0.291	0.788		
Behavioral intention	0.376	0.322	0.323	0.189	0.234	0.837	
Use Behavior	0.319	0.265	0.357	0.315	0.246	0.338	0.819

Furthermore, facilitating conditions (FC) are the extent that an individual believes that technical and organizational infrastructures support the usage of technology and system [40]. In the UTAUT model, the relationship between FCs and the usage of technology is assumed [70]; thus, the fifth hypothesis could be proposed as the following:

H5. Facilitating conditions has a positive impact on the actual use of IoT technology.

Finally, behavioral intention (BI) indicates the individual's mental readiness to be persuaded toward using technology [40]. BI is itself under the effect of numerous factors, which were mentioned before. In several researches, the effect of BI on the real use of technology was accentuated (e.g. Macedo [71]; Li et al. [72]; Cao and Niu [73]). Therefore, the sixth hypothesis could be stated as the following:

H6. Behavioral Intention has a positive impact on the actual use of IoT technology.

By considering the six proposed hypotheses above and the UTAUT model, the research conceptual model was presented in Fig. 2.

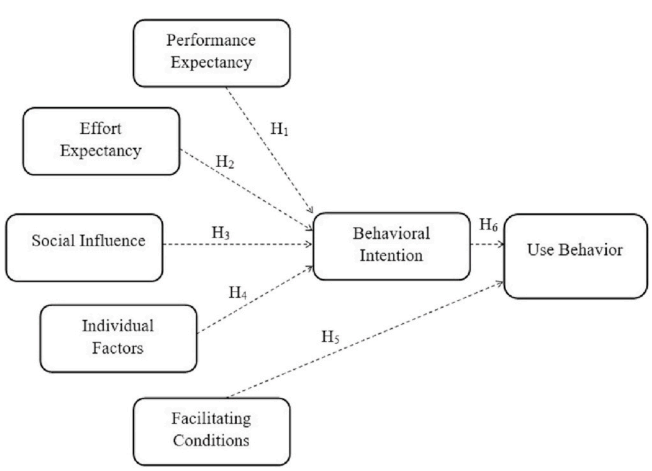

Fig. 2. Research conceptual model.

4. Results

The demographical data of the participants were presented in Table 7. According to this table most of the participants in the research have had an income below $ 600 a month and their experience was more than 10 years. In addition, 87% of the participants in the research were male.

For testing the normality of the population, Kolmogorov–Smirnov Test was carried out that was acceptable based on the significance level over 95%. As it was illustrated in Fig. 3, the values on the paths are the path coefficients and the values on the latent variables' arrows are the factor loadings. The factor loadings for the questions were statistically satisfactory and they showed that the facilitating conditions (FC) predicted 43% of the variations in the use behavior (UB). Furthermore, performance expectancy (PE) predicted 32% and effort expectancy (EE) predicted 38% of the variance in the behavioral intention (BI). Besides, social influence (SI) predicted 46% of the variance in the behavioral intention (BI) and the individual factors (IF) predicted 40% of the variance of the behavioral intention (BI).

Table 7
Demographic characteristics of the farmers.

Demographic Character		Frequency(n)	Percentile (%)
Income (USD)	<300	147	37
	300–600	112	29
	600–900	74	19
	>900	59	15
Work Experience	<5	42	11
	5–10	109	28
	>10	241	61
Age	<25	31	8
	25–35	49	13
	35–45	83	21
	45–55	154	39
	>55	75	19
Gender	Male	341	87
	Female	51	13

The calculated values for the GFI، CFI، NFI، RFI and RMSEA indices were presented in Table 8. The values demonstrated that the goodness-of-fit of the model was satisfactory.

The P-Value (<0.05) and the values of *t*-test were presented in Table 9. All the hypotheses of the research were significant in the interval level of 95%. The relationship between the individual factors (IF) and the behavioral intention (BI) was negative which means older farmers with less work experience tended more toward less application of IoT technology which was also logically acceptable.

Furthermore, according to Table 8, the positive relationship between the performance expectancy (PE) and the behavioral intentions (BI) revealed that the more the farmers have a higher expectation for the influence of IoT on their performance, they were going to be the more frequent users of IoT's equipment and facilities.

Additionally, the positive relation between the effort expectancy (EE) and the behavioral intentions (BI) showed that the perception of the farmers about the ease of IoT's use positively affected this technology usage.

On the other hand, the positive impact of the social influence (SI) on the behavioral intentions (BI) of the other farmers in the vicinity, shed light on the convincing effect of the farmers' coworkers and farmhands in persuading them to use IoT in farming.

Finally, the construction of technological infrastructure and the support of relevant public departments as well as the public facilities (facilitating conditions, FC) had positive and significant impact on the technology usage (use behavior, UB). However, based on the results, social influence (SI) had the most outstanding effect on the behavioral intentions (BI) among all the other constructs.

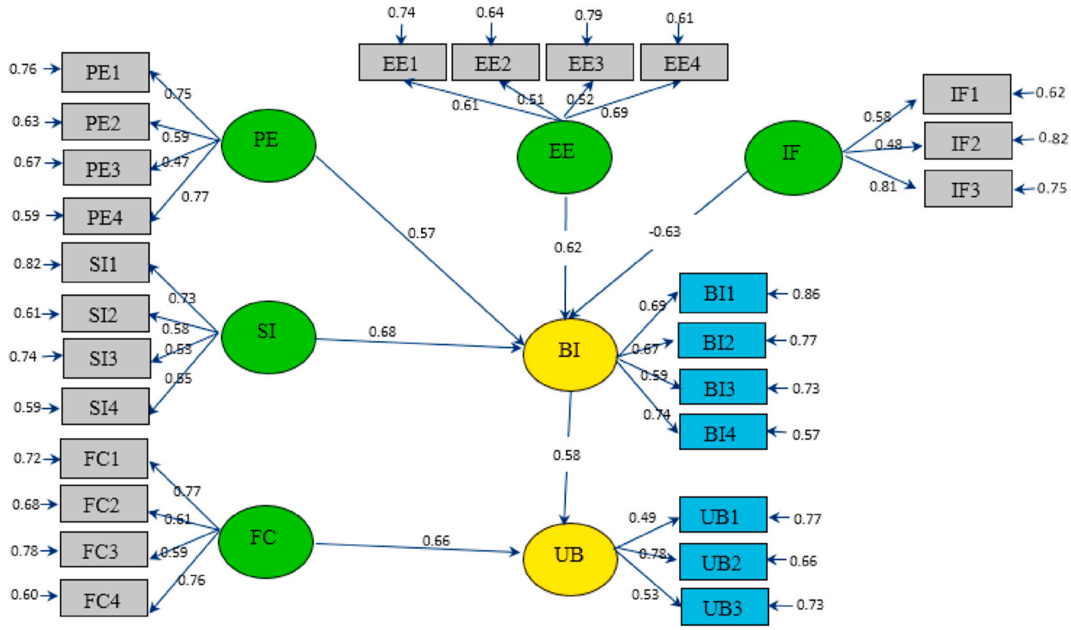

Fig. 3. Structural equations model of the research.

Table 8
Model fit statistics.

Model fit indices	
Goodness of Fit Index (GFI) > 0.90	0.92
Comparative Fit Index (CFI) > 0.90	0.93
Normed Fit Index (NFI) > 0.90	0.91
Non-Normed Fit Index (NNFI) > 0.90	0.92
Relative Fit Index (RFI) > 0.90	0.92
Standardized RMR < 0.05	0.042
Incremental Fit Index (IFI) > 0.90	0.98
root mean square error of approximation (RMSEA) < 0.080	0.054

Table 9
Structural model assessment.

Hypothesis	β	t-statistics	P-Value (<0.05)	Result
PE → BI (H_1)	0.57	5.63	.000	Supported
EE → BI (H_2)	0.62	4.91	.001	Supported
SI → BI (H_3)	0.68	3.88	.002	Supported
IF → BI (H_4)	−0.63	−3.22	.000	Supported
FC → UB (H_5)	0.66	4.74	.001	Supported
BI → UB (H_6)	0.58	6.38	.000	Supported

5. Discussions

By considering the UTAUT model in this research and the results of the research, it was revealed that performance expectancy (PE) had a positive and statistically significant effect on the behavioral intentions (BI) of the studied farmers in Iran. In other words, the more is the farmers' perception of suitable performance of IoT, the more is their motivation for its usage [74]. The result of the next hypothesis demonstrated that effort expectancy (EE) also had a positive effect on the behavioral intentions (BI) of the framers. Thus, facilitating conditions (FC) of convenience in usage and learning affect the intention to use a technology [75]. Therefore, it is noteworthy to suggest the smart gadgets' designers to design user-friendly instruments and gadgets to absorb more farmers to their smart products. On the other hand, the results of the research demonstrated that age, experience and income had negative effects on the individuals' intentions for using smart technologies in agriculture. Hence, in the elder individuals and as the age increased, acceptance of change in the work style hardly happened. Moreover, the individuals with higher income were rarely risk takers and they accepted the installation cost of modern smart technologies reluctantly. Thus, the authors suggest that insurance companies based in Iran guarantee the IoT gadgets of the framers in order to decrease the risk for them. The other results showed the statistically significant and positive impact of social influence (SI) on the intention to use technology among the farmers. In Iran as a developing country and a prevailing traditional culture farmers work in collaboration with each other in groups, therefore, group motivation for the encouragement to use IoT technology could be very beneficial in this respect. Facilitation of the conditions is also an influential factor in the usage of the IoT technology. In other words, the more is the software and hardware capabilities as well as organizational support, the more is the possibility of the usage of the technology. Therefore, it should be suggested that State Agricultural Organization in Iran as a government organization, which supervises the countrywide agriculture, should facilitate the conditions for the farmers of this country via financially supportive policies in order to financially empower the farmers to buy and install smart IoT technologies. This could be planned through long-term loans with low interest for low-income farmers. Furthermore, Ministry of I.C.T, should facilitate the necessary requisites for the farmers to use quality Internet with acceptable speed beside the establishment of private appropriate information technology networks in the farmlands to pave the way and nudge the farmers toward more technologically smart farming. In the end, it should be pointed out although some of the discovered relations of the UTAUT in the research were resembling the similar researches such as Li et al. [58] and Beza et al. [56], the technology acceptance in the context of Iran had already negatively affected due to the region droughts and the imposed sanctions against the country.

6. Recommendations

One of the preliminary limitations of the research was the application of only one model (the UTAUT model) in this research. There are numerous technology adoption models, therefore the authors recommend to the future researchers of technology usage and acceptance to test other proposed models for IoT (e.g. Shuhaiber and Mashal [76], and Gharaibeh et al. [43]) for the same contexts. Moreover, the collected data in this research– like most of the researches on the technology adoption– were based on the self-assertion of the farmers. Such an approach had a fundamental shortage that was the research conveyed the mental perceptions of the farmers from their usage and adoption of technology [77]. Furthermore, the approach in this research was statistical, we recommend that the future researchers to use other approaches such as Fuzzy approaches which do not need as mush certainty as the statistical methods [78,79]. Finally, the research was carried out in Iran as a developing country. We recommend future researchers to test the presented model of the research in a developed country to verify or moderate the results for a universal usage of IoT in agriculture.

7. Conclusion

To cast light on the answer to the research question, the research carried out in a typical Middle Eastern country (Iran) which approximately shares the same climatic conditions, quality of lands, and characteristics of farmers with many of the states in MENA and the region. The research results based on the selected theoretical model (the UTAUT model) revealed that all six hypotheses of the research were supported in the interval level of 95%. As it was evident in the research, the focal point of this research was on the farmers' intention to use IoT technology as a necessary and fundamental prerequisite for the implementation of smart farming. The supported hypotheses accentuated and proved the positive impacts of performance expectancy (**H_1**), effort expectancy (**H_2**), social influence (**H_3**), individual factors (**H_4**), and facilitating conditions (**H_5**), on the intention to use IoT technology. Moreover, the last but not least important factor was the impact of behavioral intention on the actual use of IoT technology (**H_6**). The research concludes that any planning for smart farming, which do not pay enough attention to the six above factors, could potentially fall short and do not reach its predefined goals. Therefore, a sound IT plan for the promotion of smart farming should consider first the intention of the IoT users. Then the state's agricultural policymakers should set the IoT promotion stage for the promotion of smart farming by paying attention and justifying the benefits that the farmers could achieve in respect to optimal performance, less effort, satisfaction of their personal characteristics in using technology, ease of access and use of technology even in far and remote corners of the country. Once these issues were fulfilled, the bedrock for the promotion of smart farming based on the UTAUT model was laid.

CRediT authorship contribution statement

Mohammad Hossein Ronaghi: Conceptualization, Methodology, Software, Data curation, Writing - review & editing, Visualization. **Amir Forouharfar:** Conceptualization, Methodology, Software, Data curation, Writing - review & editing, Visualization.

Conflicts of interest

The authors declare that they have no competing interests.

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Appendix 1. The research questionnaire

Code	No.	Q.	Scale				
			1	2	3	4	5
IF	1	Please specify your Gender.	Female			Male	
	2	Please specify your age.	Below 25	25–35	35–45	45–55	Above 55
	3	Please specify your monthly income.*	Below $ 300	$ 300-600	No Idea	$ 600–900	Above $ 900
	4	Please specify your work experience.	Below 5 Yrs	5–10 Yrs	No Idea		Above 10 Yrs
			Strongly Agree	**Agree**	**Unsure**	**Disagree**	**Strongly Disagree**
BI	5	I intended to use or will continue using the IoT technologies (such as Wireless Sensor Network) in the future.					
	6	I always try to use the IoT technologies in my daily works.					
	7	I planned to use or I will continue using the IoT technologies more frequently in the future.					
	8	I am going to suggest the IoT technologies use to the others farmers.					
	9	I found the IoT technologies useful in doing my farm activities.					
PE	10	Using the IoT technologies help me to accomplish my tasks more quickly than before in the farm.					
	11	Using the IoT technologies will increase my chances of achieving higher crop productivity.					
	12	If I use IoT technologies, I will increase my chances of increasing my income.					
	13	Learning how to use the IoT technologies is easy for me					
EE	14	My first impression of the IoT technologies could be described as clear, favorable and comprehensible.					
	15	I found the IoT technologies easy to use					
	16	It is applicable to me to become a skillful and deft user of the IoT technologies					
	17	People who are important to me think that I should use the IoT technologies					
SI	18	The people, who have influence on my behavior, think that I should use the IoT technologies.					
	19	The people whose opinions are valuable to me prefer to use the IoT technologies.					
	20	My near relatives, friends and acquaintances are using the IoT technologies themselves.					
	21	I have the necessary facilities for using the IoT technologies relevant to farming.					
FC	22	I have the basic knowledge on how to use the IoT technologies.					
	23						

(continued on next page)

(*continued*)

Code	No.	Q.	Scale				
			1	2	3	4	5
		IoT technology is generally compatible with the other technologies which I use currently.					
	24	I can get a help from others when I have difficulties using the IoT technologies.					
	25	I use all the relevant IoT-related applications.					
UB	26	I have a clear idea how to use the IoT systems.					
	27	I am going to use the IoT systems again.					

*Iran's currency is Rial. Since the preliminary questionnaire was in Persian and the Iranian official currency is Rial, the responses for the monthly income were converted to the equivalent price for the US Dollar. Each US dollar at the time of the study was nearly equal to 131,500 Iranian Rials.

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Availability of data and material

All data generated or analyzed during this study are included in this article.

Authors' contributions

All authors contributed equally.

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