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Analyzing Barriers to the Adoption of Climate-Smart Agriculture (CSA) by Farmers: An Application of UTAUT and Decomposed Fuzzy Approach

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ABSTRACT

Objective: Due to climate change, climate-smart agriculture (CSA) is one response to the impacts of climate change, which affect agriculture especially in developing countries. As in other sustainability transitions, technological innovation plays a vital role in implementing CSA. However, technological innovation in developing countries is progressing slowly. Farmers play a fundamental role in the adoption of CSA, but barriers reduce their willingness to implement it. Due to its geographical location, Iran also needs to implement CSA in its key agricultural regions, such as Mazandaran. This study aims to identify the barriers to CSA adoption among farmers in Mazandaran and assess their importance.

Methodology: To achieve this, the barriers to CSA adoption by farmers were identified through a literature review. The Unified Theory of Acceptance and Use of Technology (UTAUT) was used to categorize the barriers. Then, the decomposed fuzzy analytic hierarchy process (DF-AHP) method was applied to calculate the weights of the identified barriers.

Results: The study found that the most important barriers to CSA adoption by farmers in Mazandaran are “immaturity of some technologies and lack of an implementation guideline,” “Lack of sufficient skills among farmers,” and “High implementation costs and economic risk”.

Conclusion: Classifying the barriers to CSA adoption by farmers within the UTAUT model can clarify how they influence an individual's behavioral intention. In this way, it facilitates the development of strategies and the implementation of corrective actions. The study's results can be applied to regions similar to Mazandaran in terms of climatic, economic, and social conditions.

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Introduction

In 2010, the Food and Agriculture Organization of the United Nations (FAO) stated that the world's population will reach 9 billion by 2050, and that ensuring food security for this population requires increased agricultural production. However, climate change threatens the sustainability and productivity of this production (FAO, 2010). Long-term changes in temperature and precipitation patterns, part of climate change, are shifting growing seasons, altering pest and disease patterns, and expanding the range of feasible crops (Long et al., 2016). Furthermore, the special report of the Intergovernmental Panel on Climate Change (IPCC) on Global Warming states that the projected increase in global average temperature to 1.5°C above pre-industrial levels and increase in heavy rainfall will intensify the adverse effects of climate change on agriculture and water resources by 2050 (IPCC, 2018). According to these reports, although climate change will affect all countries worldwide, developing countries are more vulnerable to its consequences. That is because of the agricultural sector's importance in these countries. The impacts of climate change on agriculture threaten the economic development of developing countries and the welfare of their people (Antwi-Agyei et al., 2025).

Iran, as a developing country, is among the most vulnerable in the Middle East and North Africa (MENA) to climate change. Due to Iran's geographical location, environmental changes pose significant security challenges for this country. More than 82% of Iran is classified as arid and semi-arid regions, with annual precipitation less than one-third of the global average. Recent reports indicate that the Middle East and Iran will experience an increase in average temperature of 2.6°C and a 35% decrease in rainfall in the coming decades. Therefore, climate change in Iran and the Middle East is more severe than in other regions of the world (NCCOI, 2014). According to the Statistical Center of Iran, Iran's population will reach 91,446,000 in 2036. Hence, climate change, along with population growth, will seriously threaten food security and people's livelihoods (Statistical Center of Iran, 2023). Among Iran's provinces, Mazandaran accounts for 1.5% of the country's total area and 1.56% of its cultivated land. The province's share of the agricultural sector's value added in 2021 was 8.96%, ranking first among the country's provinces. The share of Mazandaran in wheat and rice production is 1.52% (rank 19) and 45.07% (rank 1), respectively. This fact shows the importance of this province in the agricultural sector (Statistical Center of Iran, 2023). According to the Statistical Center of Iran, the average annual rainfall in this province in 2024 was 703.2 mm, ranking third among the country's provinces. Despite the vital role of Mazandaran in supplying agricultural products, according to official reports from the National Center of Climate and Drought Crisis Management of the Iran Meteorological Organization, this province has experienced a shift in rainfall patterns from normal rains to torrential and ineffective (heavy downpour) rains. These changes have led to a 40% decrease in rainfall, a 50% decrease in river flows, and approximately a 60% decrease in water reserves behind the province's dams and reservoirs. Moreover, according to the Crisis Management Department of Mazandaran, the entire province is experiencing drought, with about 43.8% of the province's area affected by very severe drought and 32.7% by severe drought. These climate changes have directly impacted rice and wheat cultivation in Mazandaran. In rice production, climate change has shifted the growing period by 2 to 23 days earlier.

Furthermore, due to late planting dates, high temperatures, and reduced soil moisture from rainfall, rice's water requirements have increased. In wheat production, these changes have also reduced yields. This issue is particularly significant in rainfed wheat, which is more dependent on rainfall. Therefore, preserving and improving agriculture in Mazandaran Province for rice and wheat cultivation requires that agricultural production systems become more resilient, meaning they have a greater capacity to maintain optimal performance in the face of destructive events. To build resilience against climate change, the FAO proposed climate-smart agriculture (CSA) in 2010. The goal of implementing CSA is to increase productivity, adapt to climate change, and reduce greenhouse gas emissions (Antwi-Agyei et al., 2025). One of the strengths of CSA is its ability to empower farmers, who are most affected by the consequences of climate change. Access to climate-smart technologies, knowledge, and financial resources through CSA enables farmers to adapt to changing climatic conditions and improve their livelihoods (Gebremedhin et al., 2025). Despite the importance of implementing CSA and the inherent time pressures posed by climate change and related policy objectives, CSA adoption remains low. Therefore, it is essential to enhance farmers' understanding of the barriers to CSA adoption. This understanding will help in the design and implementation of CSA (Long et al., 2016). Consequently, a key issue that requires attention at the levels of policy-making, research, and practice is the analysis and reduction of barriers to the adoption of CSA technological innovations by farmers.

In the literature of agricultural technology acceptance, numerous models and theories, such as the transtheoretical model (TTM) (Doran et al., 2022), the technology acceptance model (TAM) (Alambaigi & Ahangari, 2016), and the theory of planned behavior (TPB) (Tama et al., 2021), have been proposed to explain users' behavior in adopting technology. These models examine technology acceptance at the individual level; however, each explains only a subset of the factors influencing technology adoption. For example, the TPB focuses on attitudes, subjective norms, and behavioral intention, whereas the TAM identifies perceived usefulness and perceived ease of use as the primary determinants of technology acceptance. Consequently, each of these models is unable to provide a comprehensive explanation of technology adoption behavior (Dissanayake et al., 2022). By integrating the common constructs of earlier theories, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT framework is a comprehensive model that performs better than previous models in examining technology adoption in the agricultural sector. Dissanayake et al. (2022) reviewed the literature in the field of agriculture and confirmed the superiority of this model. The foundation of UTAUT is that farmers’ intention to use a new technology mainly depends on four key beliefs: 1) how useful the technology is for their work, 2) how easy it is to use, 3) whether the necessary facilities and support are available, and 4) what others think about using it. In adopting CSA, barriers can arise across the four constructs of UTAUT, affecting farmers' behavioral intention and reducing their willingness to adopt CSA. The barriers related to these four constructs consider the outcomes of using the CSA, its implementation process, facilities, and the impact of the environment. For this reason, they lead to a comprehensive understanding of the barriers. Furthermore, this model enables a systematic examination of the farmers' CSA adoption process. Finally, classifying the barriers to CSA adoption into these four categories will help identify appropriate strategies and actions to overcome them. Given limited resources to address barriers, the importance of each barrier must be determined before implementing actions to identify which should be prioritized for elimination. In hierarchical problems, the analytic hierarchy process (AHP) method developed by Saaty (1977) is applicable. This method is based on expert judgment, which makes it sensitive to incomplete expert information and high environmental uncertainty. Decision-making under such conditions requires methods that yield more valid results. One suitable approach is the decomposed fuzzy approach developed by Cebi et al. (2022). This approach reduces the impact of incomplete expert information and environmental uncertainty by combining optimistic and pessimistic perspectives (Cebi et al., 2022). Cebi et al. (2023) developed the hybrid DF-AHP method for hierarchical decision-making problems under uncertain conditions. Based on the importance of reducing barriers to CSA adoption in developing countries, researchers have examined it in countries such as Kenya (Lenhardt et al., 2026), India (Mishra et al., 2026; Saikia et al., 2025), Costa Rica (Hugøy, 2025), and Ghana (Antwi-Agyei et al., 2025). Furthermore, few studies have investigated CSA in Iran. For example, previous studies, such as the design of a model for CSA adoption (Khademi Nosh Abadi et al., 2023) and the assessment of factors affecting CSA adoption (Etemadi et al., 2022), have been conducted in Iran. Although barriers to CSA adoption have not been investigated in Iran, in other studies, barriers to CSA adoption among farmers (individuals) have been investigated. However, they have not used a theory to examine the impact of barriers on individuals' behavioral intention. Only some of them have categorized the identified barriers into classifications such as social, economic, political, and cultural barriers (Lenhardt et al., 2026) and socio-economic, technological, and institutional (Mishra et al., 2026), but these classifications, unlike UTAUT, cannot examine the role of these barriers on individual behavior. Furthermore, in these studies, the importance of the identified barriers has not been assessed. Due to resource constraints for taking effective actions, the priority of barriers to be addressed must be determined. Accordingly, the present study is structured to achieve two key objectives. The first objective is to identify barriers to the adoption of CSA by farmers in Mazandaran, Iran. Achieving this objective requires identifying the barriers and classifying them into the four constructs of UTAUT. This classification can determine how each barrier influences individuals' behavioral intention. The second objective is to determine the importance of the identified barriers. Given the uncertainty that exists in this area, a combination of the decomposed fuzzy approach and the AHP method was used to determine the weights of the barriers.

This research includes the following sections: Section 2 presents a review of the literature and related works. The decomposed fuzzy approach and the DF-AHP method are introduced in Section 3. Section 4 describes the findings of the present study. Discussion and conclusion are presented in Sections 5 and 6, respectively.

Literature Background

Climate-Smart Agriculture

Currently, about 690 million people across the globe experience hunger. Meanwhile, many people around the globe, especially youths, are working towards solving the problem of climate change (FAO, 2021). Climate change has become an issue since the late 1990s for companies and governments (Long et al., 2016). Irregular changes in the climate result in an imbalance in weather conditions affecting agriculture (Ahmed et al., 2022). Furthermore, climate change increases the volatility of weather patterns, elevating the likelihood and severity of adverse events such as floods, storms, droughts, and rising temperatures, all of which can have detrimental effects on agriculture (Long et al., 2016). Consequently, farmers are continually at risk of crop damage from these changes (Ahmed et al., 2022). This phenomenon is especially significant for developing countries because they are heavily dependent on agriculture and thus vulnerable to the negative consequences of climate change. In turn, these changes may hinder their agricultural progress, economic development, and societal welfare (Long et al., 2016). According to scientists, climate change will lead to increased global temperatures, and this will have a hugely negative effect on agricultural productivity (Antwi-Agyei et al., 2025; Chandra et al., 2018). It has been repeatedly argued that without a serious transformation in the agricultural sector, humanity will simply struggle to meet the food demands of an estimated 9 billion people expected to populate the Earth by 2050 (Taylor, 2018). The agricultural sector will have to undergo significant transformations owing to the effects of climate change and adapt to the new weather conditions without forgetting about the reduction of greenhouse gas emissions (Long et al., 2016). Agriculture constitutes a significant portion of Gross Domestic Product (GDP) in many economies, and 2.5 billion people globally depend on this sector for their livelihoods (FAO, 2019). Achieving more productive and resilient agriculture requires transformations in the management of natural resources such as land, water, soil nutrients, and genetic resources, alongside enhancing resource use efficiency and productivity. Additionally, transitioning to such systems could contribute to climate change mitigation by increasing carbon sequestration potential and reducing greenhouse gas emissions per unit of agricultural output (FAO, 2021).

The agricultural sector needs new strategies to improve production due to changing climate conditions (Ahmed et al., 2022). Climate-Smart Agriculture (CSA) is one response to the challenges faced by agriculture due to climate change (Ahmed et al., 2022; Gebremedhin et al., 2025; Lipper et al., 2014; Long et al., 2016). CSA has quickly evolved into a key organizing concept for international organizations working at the intersection of climate change, agriculture, and development (Taylor, 2018). Describing the mechanism to tackle climate change challenges as well as food security, CSA aims to increase productivity and resilience, reduce greenhouse gas emissions, and help fulfil food security and development goals of nations (Chandra et al., 2018). To achieve this aim, three goals have been formed: (1) sustainably increasing agricultural productivity to support equitable income growth, food security, and development; (2) enhancing adaptability and resilience to climate change at both the farm and national levels; and (3) developing opportunities to reduce greenhouse gas emissions from agriculture relative to past trends (Ahmed et al., 2022; Gebremedhin et al., 2025; Lipper et al., 2014; Long et al., 2016). Figure 3 shows the three Pillars of Climate-Smart Agriculture (Saikia et al., 2025). Although CSA aims to achieve all three objectives, this does not imply that every action implemented in every location must yield a “triple win”. CSA necessitates consideration of all three objectives across local to global scales and over both short-term and long-term horizons to arrive at contextually acceptable solutions (Lipper et al., 2014). This approach encompasses several dimensions that facilitate the optimization of sustainable agricultural processes, including (Ahmed et al., 2022):

- **Food Security:** Provision of food security for all people to ensure that everyone is physically, socially, and economically able to gain sufficient food that is safe and nutritious enough to lead an active and healthy life.
- **Production:** Improving food security and the efficiency of production systems (productivity) through advancements that reduce greenhouse gas emissions and enhance sustainability.
- **Capacity Building:** Helping to create adaptive measures, increasing productivity, and increasing resistance to climate change
- **Emission Reduction:** Efforts geared towards minimizing or stopping emissions of greenhouse gases to improve the carbon sequestration capabilities of trees and soils.
- **New Technologies:** Using new technologies to increase productivity and income, especially when it comes to monitoring climate change and reducing greenhouse gas emissions.

- **Transformation:** Through these actions, food security is improved by transforming agricultural systems in response to climate change
- **Vulnerability Reduction:** Agricultural systems should improve their ability to cope with climate change while at the same time increasing productivity and reducing greenhouse gas emissions.

Such practices include, for example, agroforestry and the enhancement of crop varieties that aim to offset the adverse effects of climate change through carbon sequestration. The implementation of CSA would depend on the geographical location and would require solutions that are customized based on the particular socio-economic and environmental situation of the region (Gebremedhin et al., 2025).

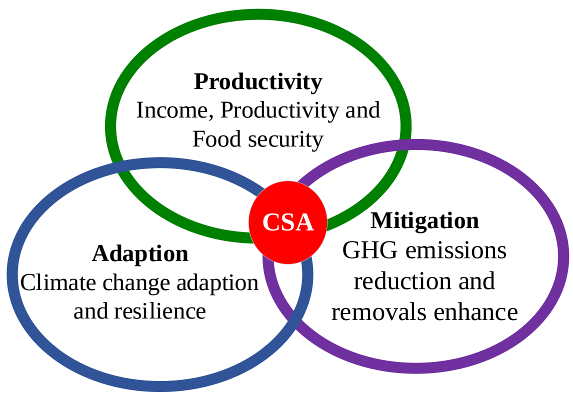

Figure 1. The three pillars of CSA (Saikia et al., 2025)

Unified Theory of Acceptance and Use of Technology (UTAUT)

Research on the acceptance and dissemination of technology is considered a mature area of inquiry in the Information Systems (IS) literature. Scholars in this field are continuously striving to understand the various factors influencing individual acceptance and use of emerging information technologies (Tamilmani et al., 2021). Based on this, Venkatesh et al. (2003) compared and tested variables across eight different technology acceptance models and subsequently proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) (Im et al., 2011). This model includes the following: the Technology Acceptance Model (TAM) (Davis, 1989); the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1977); the Motivational Model (MM) (Davis et al., 1992); the Theory of Planned Behavior (TPB) (Ajzen, 1991); the Combined TAM and TPB Model (C-TAM-TPB) (Taylor & Todd, 1995); the Model of PC Utilization (MPCU) (Thompson et al., 1991); the Innovation Diffusion Theory (IDT) (Moore & Benbasat, 1991); and the Social Cognitive Theory (SCT) (Compeau & Higgins, 1995). This model addresses more rational scenarios regarding technology acceptance. The UTAUT model has successfully identified relationships among task-technology, social influence, and resource accessibility within facilitating conditions. In other words, this model exhibits greater explanatory power than other models and theories (Dissanayake et al., 2022). The UTAUT model consists of four main variables: performance expectancy, effort expectancy, social influence, and facilitating conditions, alongside four moderating variables related to gender, age, experience, and voluntariness of use (Im et al., 2011; Venkatesh et al., 2012). In this context, performance expectancy indicates the users' beliefs on how beneficial it is to perform certain tasks through technology; effort expectancy reveals how easy it is for a user to use the technical means; social influence shows how much the user feels that important other people expect him/her to use particular technical means; facilitating conditions highlight users' perceptions of available facility and resources to make certain actions. According to UTAUT, performance expectancy, effort expectancy, and social influence are theorized to affect behavioral intention to use technology, while behavioral intention and facilitating conditions determine technology use. Additionally, individual difference variables—namely, age, gender, and experience—are considered moderators (Venkatesh et al., 2003). Despite its limitations, the UTAUT model is significant because it integrates eight foundational theories and has been validated on a large, real-world dataset (Im et al., 2011). Figure 2 illustrates the UTAUT model.

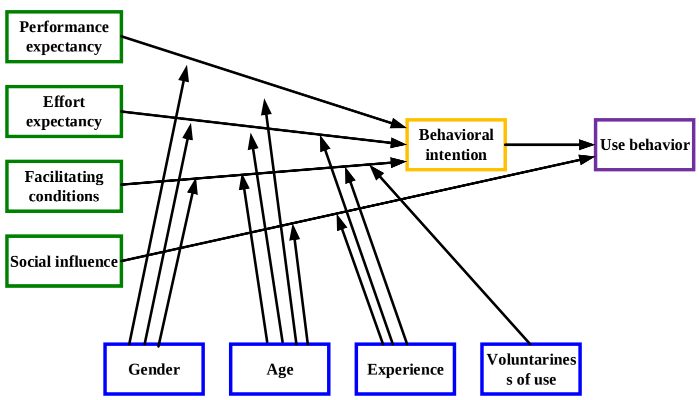

Figure 2. UTAUT model (Venkatesh et al., 2003)

Related works

Given the need to investigate the effects of climate change and global warming on agriculture, numerous studies have been conducted across different countries. In 2026, two studies examined the barriers to the adoption of CSA in India and Kenya. Lenhardt et al. (2026) identified social, economic, political, and cultural barriers to CSA adoption in southern Kenya. Using the five-stage process-tracing technique with Bayesian updating, this study revealed that although farmers are inclined to adopt CSA practices, the lack of communication between farmers and public and private officials—who primarily emphasize education and training—has reduced their uptake. Consequently, based on qualitative data, poverty and limited access to financial resources were identified as the most significant barriers to CSA adoption. Furthermore, Mishra et al. (2026) conducted a study in 2026, categorizing CSA adoption barriers into three categories: socio-economic, technological, and institutional. Analysis of survey data collected from farmers found that factors such as a lack of financial resources, inadequate land-related infrastructure, and limited knowledge and skills are the primary barriers to promoting CSA. This study also emphasized awareness of climate change and the need for integrated policies that facilitate financial access, capacity building, and institutional support to strengthen agricultural systems. In 2025, five studies identified and examined the challenges and barriers to CSA in India, China, Norway, Costa Rica, Ghana, and East Africa. In one of these studies, Saikia et al. (2025) identified 22 CSA barriers through analysis of primary data from several farmers. The findings indicated that younger farmers with higher levels of education and better access to infrastructure are more likely to adopt CSA. Additionally, the results showed that CSA adoption has led to improved crop yield, farm income, and food security. Another study in 2025, Wang et al. (2025), investigated CSA barriers using the Multidimensional Dynamic Decision Analysis Framework (MDDAF) approach among farmers in the black soil region of Northeast China. In this study, farmers' decision-making processes at various stages of CSA adoption were analyzed, taking into account factors such as technology, decision-making processes, livelihood capital, livelihood outcomes, political and institutional contexts, and vulnerability contexts. The findings revealed that traditional norms, economic constraints, policy incoherencies, climate risks, and land tenure issues are among the most significant barriers. This study also emphasized the need for targeted training, risk management, and the professionalization of agricultural services to facilitate more effective CSA adoption. Furthermore, Hugøy (2025) identified CSA indicators and challenges in Norway and Costa Rica, addressing discrepancies between formal CSA approaches and farmers' agricultural practices. The results indicated that CSA's emphasis on quantitative indicators is inconsistent with practical farming methods. Moreover, although CSA is considered a useful approach for enhancing agricultural sustainability and resilience, it fails to attract long-term policy support due to difficulties in measurement and assessment. In another study in 2025, Antwi-Agyei et al. (2025) examined barriers to the successful adoption of CSA by smallholder farmers. The results showed that issues related to budget, political information, infrastructure, human resources, and, particularly, environmental, socio-cultural, and economic factors constrain organizations from adopting CSA. Additionally, a study by Gebremedhin et al. (2025) that employed a systematic literature review identified opportunities and challenges for CSA in East Africa. The findings indicated that institutional barriers, drought, and socio-economic inequality are among the most significant barriers to CSA adoption. This study highlighted the role of stakeholder participation and knowledge dissemination in the adoption and adaptation of CSA.

In 2024, two studies also evaluated the challenges and barriers to CSA. In the first study, Pedersen et al. (2024) surveyed 69 stakeholders in five European food supply chains, including wheat, apple, potato, and onion production, and organic dairy, to examine the factors influencing the adoption of CSA. The results of this study showed that economic, institutional, and policy factors, as well as individual and psychological characteristics, are the most important drivers of CSA adoption. On the other hand, economic constraints, technological barriers, and institutional and policy weaknesses were identified as the most significant barriers to adopting this approach. The findings indicate that high investment costs, lack of financial incentives, limited market demand for climate-smart products, the complexity of new technologies, and policy inconsistencies can make the adoption of CSA difficult. The second study, Raihan et al. (2024), conducted a comprehensive review of the concepts and challenges of CSA. The results of this study showed that emerging technologies such as remote sensing, Internet of Things (IoT), and artificial intelligence play an important role in improving the efficiency and sustainability of agricultural systems and can contribute to the development of CSA through accurate monitoring of farm conditions, optimal input management, crop yield prediction, climate risk reduction, and improved farmer decision-making. However, barriers such as high costs of implementing technologies, the need for appropriate technical infrastructure, challenges related to data security and quality, limited access of farmers to advanced technologies, and lack of specialized knowledge and skills are considered to be the most important barriers to the expansion of this approach. In previous years, two studies conducted in 2022 in Iran and one study conducted in 2016 across five European countries examined CSA. Etemadi et al. (2022), who carried out their study in Iran in 2022, investigated factors influencing the adoption of CSA strategies in Fars Province. In this research, strategies were categorized into three groups: water and input management, soil fertility enhancement and maintenance, and a combination of these two strategies. The results demonstrated that psychological characteristics, including beliefs about climate variability and risk perception, have a significant impact. It was also found that younger farmers, due to their greater understanding of CSA and higher income aspirations, are more willing to adopt CSA strategies. In another study, Khademi Nosh Abadi et al. (2023) in Iran designed a conceptual model for the application of CSA technology emphasizing motivational factors in Alborz Province using Bayesian structural equation modeling. The findings indicated that motivational factors, including subjective norms, perceived behavioral control, and descriptive norms, have a significant effect on CSA adoption. Finally, the 2016 study by Long et al. (2016) examined key socio-economic barriers from both supply and demand perspectives in Europe. This research demonstrated that socio-economic barriers constitute the primary barrier to CSA adoption within the agricultural supply chains of five European countries. Table 1 summarizes the studies mentioned.

Table 1. Literature review

Author (Year)	Aim	Method	Case Study	Result
Lenhardt et al. (2026)	Identifying leading barriers to CSA uptake	Collier's four standard process-tracing causal tests	Southern Kenya	They categorized the barriers as follows: • Social; • Economic; • Political; • Cultural. The most significant barriers identified include the following: • Poverty; • Limited access to financial resources.
Mishra et al. (2026)	Examining barriers to the adoption of CSA among smallholder farmers	Ordered Logistic Regression (OLR)	Odisha, India	They categorized the barriers as follows: • Economic; • Technological; • Institutional. The most significant barriers identified include the following: • lack of financial resources; • inadequate land-related infrastructure; • limited knowledge; • limited skills.
Saikia et al. (2025)	Assessing adaptation, impact, and barriers to CSA	Binary Logistic Regression	Arunachal Pradesh, India	The 22 barriers identified include the following: • Poor extension services; • Low level of awareness of CSA practices; • Lack of access to productive farm inputs; • Lack of or inadequate land; • And so on
Wang et al. (2025)	Analyzing barriers to CSA adoption	MDDAF	Northeast China's black soil region	They categorized the barriers as follows: • Technology; • Decision-making processes; • Livelihood capital; • Livelihood outcomes; • Political; • Institutional contexts; • Vulnerability contexts. The most significant barriers identified include the following: • Traditional norms; • Economic constraints; • Policy incoherencies; • Climate risks; • Land tenure issues.

Hugøy (2025)	Evaluating CSA metrics and challenges for agroecology	Ethnographic	Norway and Costa Rica	They identified some barriers indirectly as follows: • Traditional knowledge vs. scientific practices; • Economic constraints; • Skepticism towards new technologies; • Institutional challenges; • Measurement and calculation limitations; • Challenges of standardization.
Antwi-Agyei et al. (2025)	Investigating barriers and knowledge gaps to CSA and climate information services: a multi-stakeholder analysis of smallholder farmers' uptake	Interviews	Ghana	They identified some barriers as follows: • Budget; • Political information; • Infrastructure; • Human resources; • Particularly environmental; • Socio-cultural; • Economic factors constrain; • Organizations.
Gebremedhin et al. (2025)	Exploring challenges and opportunities of climate change mitigation through CSA	Systematic Literature Review	East Africa	The most significant barriers identified include the following: • Institutional barriers; • Drought; • Socio-economic inequality.
Pedersen et al. (2024)	Identifying barriers to CSA practices and technologies adoption in five European food supply chains	Semi-structured Interviews	Germany, Lithuania, Spain, the Netherlands, and Denmark	They categorized the barriers as follows: • Personal barriers; • Technological or practice-related barriers; • Social barriers; • Institutional and policy barriers; • Economic barriers; • Informational barriers. The most significant barriers identified include the following: • High investment costs; • Lack of financial incentives; • Limited market demand for climate-smart products; • The complexity of new technologies; • Policy inconsistencies.
Raihan et al. (2024)	Reviewing the latest developments and barriers for CSA	Systematic Literature Review	-	The most significant barriers identified include the following: • High costs of implementing technologies; • The need for appropriate technical infrastructure;

				• Challenges related to data security and quality; • Limited access of farmers to advanced technologies; • Lack of specialized knowledge and skills.
Khademi Nosh Abadi et al. (2023)	Designing a behavioral intention model for the adoption of CSA technology in wheat farms	Modeling Bayesian Approach	Alborz in Iran	They identified some motivational factors that affect CSA adoption, as follows: • Subjective norms; • Perceived behavioral control; • Descriptive norms.
Etemadi et al. (2022)	Assessing factors affecting the adoption of CSA strategies with emphasis on social and psychological capital characteristics	Multinomial Logit Model	Fars in Iran	They identified the adoption of CSA strategies as follows: • Water and input management; • Soil fertility enhancement and maintenance; • A combination of these two strategies. They identified psychological characteristics that affect CSA adoption as follows: • The belief in climate variability; • Risk perception.
Long et al. (2016)	Analyzing barriers to the adoption and diffusion of technological innovations for CSA in Europe	Interviews & Coding of typical and frequently mentioned elements	Netherlands, France, Italy, and Switzerland.	They identified the most significant barrier as key socio-economic barriers from both supply and demand perspectives.

A review of the existing literature on CSA reveals several significant gaps. Firstly, it shows that some studies have been conducted in developed countries (Hugøy, 2025; Long et al., 2016), while several research have taken place in developing countries (Antwi-Agyei et al., 2025; Etemadi et al., 2022; Khademi Nosh Abadi et al., 2023; Wang et al., 2025). In addition, some studies have been conducted in underdeveloped nations (Gebremedhin et al., 2025; Saikia et al., 2025). Furthermore, it is vital to emphasis that all of these studies employed simple research methods, such as interviews and questionnaires, without any decision-making analysis (Antwi-Agyei et al., 2025; Etemadi et al., 2022; Gebremedhin et al., 2025; Hugøy, 2025; Khademi Nosh Abadi et al., 2023; Long et al., 2016; Saikia et al., 2025; Wang et al., 2025). In contrast, this study uses a quantitative analysis based on a multi-phase mixed-methods framework. Specifically, the questionnaire data are analyzed within the analytic hierarchy process (AHP), and to account for the ambiguity and uncertainty inherent in agricultural systems, a decomposed fuzzy approach is employed. Apart from a lack of decision-making methods, previous studies have not considered uncertainty management. It means there has been no effort to model the behavioral and environmental complexities in farmers' decision-making. In other words, within the context of developing countries—which share similar climatic, economic, and social conditions with the present study—researchers have merely identified the factors influencing the adoption of CSA using descriptive statistics or regression, without considering the uncertainties in prioritizing factors, the nonlinear relationships among variables, or varying levels of ambiguity in expert judgments. An important point raised in subjective MADM methods, such as AHP, is the uncertainty present in the environment and the incomplete information (Mohseni et al., 2025). This uncertainty affects experts' judgment. To reduce this effect, approaches such as grey and fuzzy have been developed. Among previous studies on barriers to CSA adoption, no one has used these approaches. Some of these extensions handle uncertainty using membership, as seen in Type-2 fuzzy sets, or through both membership and non-membership, as used in Pythagorean fuzzy sets and spherical fuzzy sets (Kahraman & Haktanır, 2024)

There is a common problem in the data collection of all the mentioned fuzzy approaches. In these approaches, only a positive question is asked, and responses are recorded based on degrees of membership and non-membership. For example, the expert is asked how much more important A is than B. However, the human mind considers both positive and negative aspects when making a judgment. The decomposed fuzzy approach, an extension of fuzzy, developed by Cebi et al. (2022). It addresses the mentioned issue by considering two perspectives: positive (optimistic) and negative (pessimistic). The optimistic approach emphasizes the completeness of a situation, whereas the pessimistic approach highlights its emptiness. Although these two perspectives are mathematically complementary, they do not always integrate into a unified viewpoint when interpreted by humans. Therefore, by capturing variations in decision-makers' attitudes, decomposed fuzzy sets enhance evaluation accuracy (Arslan & Cebi, 2024). Besides, from a computational complexity perspective, decomposed fuzzy is less complex to calculate than current fuzzy extensions, offering better accuracy in decision analysis. Finally, some research efforts have focused only on identifying factors influencing smart agriculture, neglecting to adopt a theoretical perspective for a comprehensive analysis (Antwi-Agyei et al., 2025; Etemadi et al., 2022; Gebremedhin et al., 2025; Hugøy, 2025; Khademi Nosh Abadi et al., 2023; Long et al., 2016; Saikia et al., 2025; Wang et al., 2025). This shortfall in analytical approach underscores the necessity for a greater emphasis on theoretical frameworks in future research endeavors. Overall, it seems essential to adopt less superficial and more comprehensive and theoretical approaches for advancing future studies in this domain.

Barriers to Adoption of CSA

By examining the challenges and barriers identified in the mentioned articles, the barriers have been categorized according to the UTAUT model as follows (Figure 3):

Performance Expectancy (PE): Performance expectancy is the extent to which an individual believes that using a technology will improve their performance. It reflects the perceived usefulness and value of the technology in achieving goals (Venkatesh et al., 2003). Therefore, this category includes barriers that reduce farmers' perceptions of the benefits and value of using CSA.

- **Time-consuming practices (PE_1):** The time-consuming and labor-intensive nature of CSA practices, such as composting and straw mulching, hinders their widespread adoption, in conditions of young labor force shortages (Saikia et al., 2025).
- **Trade-off among the three objectives of CSA (PE_2):** A trade-off often exists among the three main objectives of CSA. Therefore, it is not possible to achieve the optimal level for all three objectives (Gebremedhin et al., 2025; Lou et al., 2024).
- **Ecological mismatches (PE_3):** Uniform CSA strategies may ignore the specific ecological and socio-economic conditions across regions (e.g., spring warming delays, waterlogging in low-lying areas, soil compaction in clay soils) (Antwi-Agyei et al., 2025; Gebremedhin et al., 2025).

Effort Expectancy (EE): Effort expectancy suggests that the easier a technology is to use and the less effort it requires, the more likely it is to be adopted (Venkatesh et al., 2003). Therefore, any barriers that make the use of CSA difficult for farmers fall into this category.

- **Difficulty in monitoring CSA outcomes (EE_1):** Measuring and monitoring the impacts of CSA is challenging and subject to uncertainty (Gebremedhin et al., 2025; Hugøy, 2025; Lou et al., 2024).
- **Immaturity of some technologies and lack of an implementation guideline (EE_2):** Some technologies remain immature, or there are no clear guidelines for their dissemination and implementation (Lou et al., 2024; Wang et al., 2025).
- **Lack of standard indicators and evaluation criteria (EE_3):** Standard indicators and evaluation frameworks for assessing CSA performance have not been sufficiently developed (Gebremedhin et al., 2025; Lou et al., 2024).

Facilitating Conditions (FC): Facilitating conditions refer to the extent to which individuals believe that the technical, organizational, and resource-related infrastructures are available to support the use of a technology (Venkatesh et al., 2003). Therefore, barriers in this category include limitations and resource constraints that hinder the use of CSA.

- **Lack of sufficient skills among farmers (FC_1):** Farmers lack enough capacity to understand and use climate information and agricultural innovations. Consequently, they tend to continue using traditional methods, and the adoption of CSA among them decreases (Ahmed et al., 2022; Antwi-Agyei et al., 2025; Baffour-Ata et al., 2025; Gebremedhin et al., 2025; Hugøy, 2025; Lenhardt et al., 2026; Long et al., 2016; Mishra et al., 2026; Saikia et al., 2025; Wang et al., 2025).

- **Superficial knowledge and fragmented perception (FC_2):** Farmers have only superficial awareness of CSA. They reduce CSA to isolated components such as "no-till" or "straw mulching", without a proper understanding of the interactions among these components (Antwi-Agyei et al., 2025; Gebremedhin et al., 2025; Hugøy, 2025; Mishra et al., 2026; Saikia et al., 2025; Wang et al., 2025).
- **High implementation costs and economic risk (FC_3):** High initial costs and uncertain economic conditions reduce farmers' willingness to adopt CSA practices (Antwi-Agyei et al., 2025; Baffour-Ata et al., 2025; Gebremedhin et al., 2025; Long et al., 2016; Lou et al., 2024; Saikia et al., 2025; Wang et al., 2025).
- **Farmers' lack of access to resources and technology (FC_4):** Farmers face constraints in accessing the financial resources and technologies necessary for CSA implementation. Furthermore, the government does not support CSA implementation (Ahmed et al., 2022; Antwi-Agyei et al., 2025; Baffour-Ata et al., 2025; Gebremedhin et al., 2025; Hugøy, 2025; Lenhardt et al., 2026; Long et al., 2016; Mishra et al., 2026).

Social Influence (SI): Social influences relate to how much an individual perceives that important individuals and groups think that he or she should use the technology (Venkatesh et al., 2003). As such, barriers under this category will be those that make the influential individuals discourage the adoption of CSA by farmers.

- **Cognitive biases (SI_1):** Farmers hold incorrect beliefs about CSA. For example, farmers believe that straw mulching prevents seed-soil contact and germination, or that no-till leads to soil hardening and inhibits root penetration, whereas scientific evidence indicates the contrary (Wang et al., 2025).
- **CSA's dependence on policies and institutions (SI_2):** Successful CSA implementation is largely dependent on supportive policies, institutional coordination, and governance structures (Antwi-Agyei et al., 2025; Baffour-Ata et al., 2025; Gebremedhin et al., 2025; Hugøy, 2025; Long et al., 2016; Mishra et al., 2026; Wang et al., 2025).
- **Low consumer demand for environmentally friendly products (SI_3):** The adoption of CSA technologies increases production costs, leading to a decrease in demand for these products (Long et al., 2016).
- **Kinship network enforcement (SI_4):** Kinship networks both transmit information and, due to their homogeneity, reinforce traditional norms. For instance, a farming father who himself encouraged CSA may refuse to see a no-till field (Wang et al., 2025).

- **Social norms and stigmatization (e.g., "lazy farming") (SI_5):** Farmers perceive traditional farming as meticulous and associate CSA with laziness (Mishra et al., 2026; Saikia et al., 2025; Wang et al., 2025).
- **Land tenure disputes and boundary ambiguity (SI_6):** Visual markers of plot boundaries disappear in flat cultivation, leading to gradual land encroachment by neighbors and the emergence of ownership disputes (Saikia et al., 2025; Wang et al., 2025).

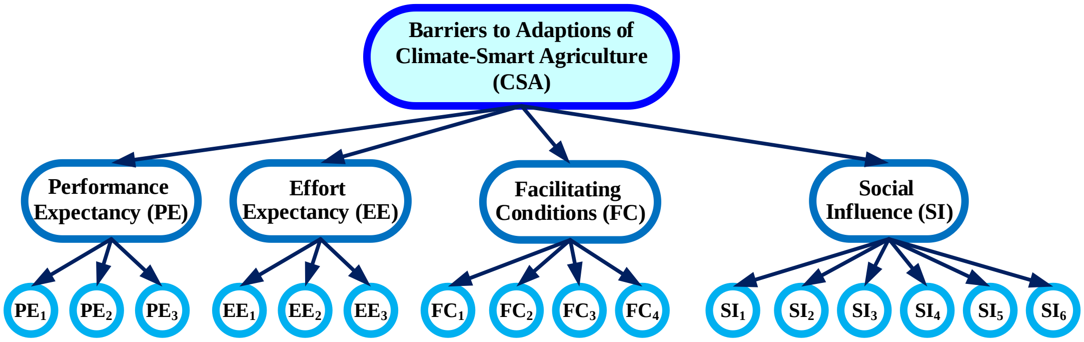

Figure 3. Hierarchical structure of barriers within the constructs of UTAUT

Materials and Methods

The present research was structured to analyze the barriers to CSA implementation in the north of Iran. In other words, this study aims to identify the barriers that affect farmers' adoption of CSA in this region. To achieve this goal, first, through a literature review in the research area, the barriers to CSA implementation were identified. The identified barriers were then classified into the four constructs of UTAUT. In the next step, the DF-AHP method was used to determine the importance of barriers in farmers' adoption of CSA. This method combines a new fuzzy approach with the AHP, providing more reliable results in high-uncertainty contexts. For this purpose, a questionnaire was designed, and 6 farmers who had experience working in the north of Iran were asked to complete it. It is worth noting that, due to this method's robustness, a large number of experts is not required (Arslan et al., 2023; Cebi et al., 2023; Moslem et al., 2024). These farmers had more than 10 years of experience in agriculture and had also studied in fields related to agriculture. Information about the experts is provided in Table 2.

Table 2. Characteristics of the experts

Characteristics / Experts	Work experience (Years)	Field of study	Academic degree
Expert 1	10	Agricultural engineering	PhD
Expert 2	11	Agricultural engineering	BC
Expert 3	14	Agricultural engineering	BC
Expert 4	20	Agricultural management	MA
Expert 5	15	Agricultural engineering	BC
Expert 6	25	Agricultural management	MA

Finally, after data collection, the importance of the barriers was determined using the DF-AHP method. Figure 4 indicates the framework of the present research.

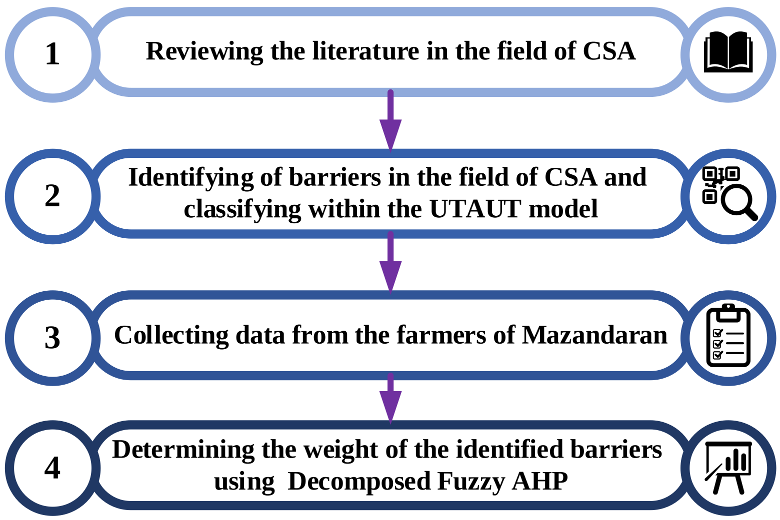

Figure 4. Research framework

First, the decomposed fuzzy approach is introduced, followed by a description of the steps of DF-AHP.

Preliminaries of Decomposed Fuzzy Sets (DFS)

Cebi et al. (2022) introduced decomposed fuzzy sets (DFS) as an extension of intuitionistic fuzzy sets. In multi-criteria decision-making (MCDM) problems, linguistic evaluations are obtained by asking questions to decision-makers. DFS handles these questions from two perspectives of optimistic approach (O) and the pessimistic approach (P), and increases the quality of the collection of expert opinions (Cebi et al., 2022). While the O approach is concerned with the bright side of things, the P approach centers on the negative aspect. The two approaches are complementary mathematically but do not necessarily add up to form one viewpoint. Thus, through accounting for variations in the attitudes of decision makers, DFS enhances evaluation accuracy (Arslan & Cebi, 2024). The following part provides the foundational, preliminary, and definition concepts related to DFS, as presented by Cebi et al. (2022).

Definition 1. A decomposed fuzzy set assigns membership ($\boldsymbol{\mu}_{\tilde{A}}$) and non-membership ($\boldsymbol{\vartheta}_{\tilde{A}}$) degrees to each element from both optimistic and pessimistic perspectives, such that, in each perspective, the sum of the membership and non-membership degrees satisfies $\mathbf{0} \leq \boldsymbol{\mu}^{\mathrm{o}}_{\tilde{A}} + \boldsymbol{\vartheta}^{\mathbf{o}}_{\tilde{A}} \leq 1$ and $\mathbf{0} \leq \boldsymbol{\mu}^{\mathbf{p}}_{\tilde{A}} + \boldsymbol{\vartheta}^{\mathbf{p}}_{\tilde{A}} \forall \leq 1$.

Definition 2. Two numbers $\tilde{\alpha}_1 = \{O(a_1, b_1), P(c_1, d_1)\}$ and $\tilde{\alpha}_2 = \{O(a_2, b_2), P(c_2, d_2)\}$ are decomposed fuzzy numbers. Based on them, the basic operations are as Eq. (1-4):

Addition:

$$\tilde{\alpha}_1 \oplus \tilde{\alpha}_2 = \left\{O\left(\frac{a_1 + a_2 - 2a_1a_2}{1 - a_1a_2}, \frac{b_1 + b_2 - 2a_1a_2}{b_1 + b_2 - b_1b_2}\right), P(c_1 + c_2 - c_1c_2, d_1d_2,)\right\} \tag{1}$$

Multiplication:

$$\tilde{\alpha}_1 \otimes \tilde{\alpha}_2 = \left\{O(a_1a_2, b_1 + b_2 - b_1b_2), P\left(\frac{c_1c_2}{c_1 + c_2 - c_1c_2}, \frac{d_1 + d_2 - 2d_1d_2}{1 - d_1d_2}\right)\right\} \tag{2}$$

Multiplication by a scalar:

$$\lambda. \tilde{\alpha} = \left\{O\left(\frac{\lambda a}{(\lambda - 1)a + 1}, \frac{b}{\lambda - (\lambda - 1)b}\right), P\big((1 - (1 - c)^{\lambda}), d^{\lambda}\big)\right\} \; for \; \lambda > 0 \tag{3}$$

λth power of $\tilde{\alpha}$, $\lambda > 0$:

$$\tilde{\alpha}^{\lambda} = \left\{O\big(a^{\lambda}, (1 - (1 - b)^{\lambda})\big), P\left(\frac{c}{\lambda - (\lambda - 1)c}, \frac{\lambda d}{(\lambda - 1)d + 1}\right)\right\} \; for \; \lambda > 0 \tag{4}$$

Definition 3. If $\lambda, \lambda_1, \lambda_2 > 0$ then:

$$\tilde{\alpha}_1 \oplus \tilde{\alpha}_2 = \tilde{\alpha}_2 \oplus \tilde{\alpha}_1 \tag{5}$$

$$\tilde{\alpha}_1 \otimes \tilde{\alpha}_2 = \tilde{\alpha}_2 \otimes \tilde{\alpha}_1 \tag{6}$$

$$\lambda(\tilde{\alpha}_1 \oplus \tilde{\alpha}_2) = \lambda\tilde{\alpha}_1 \oplus \lambda\tilde{\alpha}_2 \tag{7}$$

$$(\tilde{\alpha}_1 \otimes \tilde{\alpha}_2)^{\lambda} = \tilde{\alpha}_1^{\lambda} \otimes \tilde{\alpha}_2^{\lambda} \tag{8}$$

$$\lambda_1. \tilde{\alpha} \oplus \lambda_2. \tilde{\alpha} = (\lambda_1 + \lambda_2). \tilde{\alpha} \tag{9}$$

$$\tilde{\alpha}^{\lambda_1} \otimes \tilde{\alpha}^{\lambda_2} = \tilde{\alpha}^{(\lambda_1 + \lambda_2)} \tag{10}$$

Definition 4. If $\tilde{\alpha}_i = \{O(a_i, b_i), P(c_i, d_i)\}$ and $\lambda_i = \lambda_1, \lambda_2, \ldots, \lambda_n$; $\lambda_i \in [0,1]$; $\sum_{i=1}^{n} \lambda_i = 1$, then the Decomposed Weighted Arithmetic Mean (DWAM) is calculated as Eq. (11):

$$DWAM\ (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_n) = \lambda_1.\tilde{\alpha}_1 \oplus \lambda_2.\tilde{\alpha}_2 \oplus \dots \oplus \lambda_n.\tilde{\alpha}_n$$
$$= \left\{ O\left(\frac{\sum_{i=1}^{n} \lambda_i a_i}{1 + \sum_{i=1}^{n} (\lambda_i a_i - \frac{a_i}{n}}, \frac{\prod_{i=1}^{n} b_i}{\sum_{i=1}^{n} b_i^{n-1} \lambda_i (1 - b_i) + \prod_{i=1}^{n} b_i} \right), P\left(\left(1 - \prod_{i=1}^{n} (1 - c_i)^{\lambda_i} \right), \prod_{i=1}^{n} d_i^{\lambda_i} \right) \right\} \tag{11}$$

Definition 5. If $\tilde{\alpha}_i = \{O(a_i, b_i), P(c_i, d_i)\}$ and $\lambda_i = \lambda_1 a, \lambda_2, \dots, \lambda_n; \lambda_i \in [0,1]; \sum_{i=1}^{n} \lambda_i = 1$, then the Decomposed Weighted Geometric Mean (DWGM) is calculated as Eq. (12):

$$DWGM\ (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_n) = \tilde{\alpha}_1^{\lambda_1} \otimes \tilde{\alpha}_2^{\lambda_2} \otimes \dots \otimes \tilde{\alpha}_n^{\lambda_n}$$
$$= \left\{ \begin{array}{c} O\left(\prod_{i=1}^{n} \tilde{\alpha}_1^{\lambda_1}, \left(1 - \prod_{i=1}^{n} (1 - b_i)^{\lambda_i} \right) \right), \\ P\left(\frac{\prod_{i=1}^{n} c_i}{\sum_{i=1}^{n} c_i^{n-1} \lambda_i (1 - c_i) + \prod_{i=1}^{n} c_i}, \frac{\sum_{i=1}^{n} \lambda_i d_i}{1 + \sum_{i=1}^{n} (\lambda_i d_i - \frac{d_i}{n})} \right) \end{array} \right\} \tag{12}$$

Definition 6. Let $\tilde{\alpha} = \{O(a, b), P(c, d)\}$. The consistency index (CI) is defined as Eq. (13):

$$CI(\tilde{\alpha}) = 1 - \sqrt{\frac{(a - d)^2 + (b - c)^2 + (1 - a - b)^2 + (1 - c - d)^2}{2}} \tag{13}$$
$$0 \leq CI(\tilde{\alpha}) \leq 1$$

If the consistency index ($CI(\tilde{\alpha})$) is closer to 1, the consistency of the decision-maker is greater.

Definition 7. Let $\tilde{\alpha} = \{O(a, b), P(c, d)\}$. The score index (SI) is defined as Eq. (14):

$$SI(\tilde{\alpha}) = \begin{cases} \frac{(a + b - c + d).CI(\tilde{\alpha})}{2k} & SI(\tilde{\alpha}) > 0 \\ 0 & SI(\tilde{\alpha}) \leq 0 \end{cases} \tag{14}$$

Where k is the linguistic scale multiplier.

If a standard linguistic scale is used in a study, where you pull fuzzy numbers from a standard table, the value k is obtained as Eq. (15-16):

$$k = \frac{(a_{max} + b_{min} - c_{min} + d_{max}).\, CI^*(\tilde{\alpha})}{2k} \tag{15}$$

$$CI^*(\tilde{\alpha}) = \sqrt{\frac{(a_{max} - d_{min})^2 + (b_{min} - c_{min})^2 + (1 - a_{max} - b_{min})^2 + (1 - c_{min} - d_{max})^2}{2}} \tag{16}$$

Here $\tilde{\alpha} = \{O(a_{max}, b_{min}), P(c_{min}, d_{max})\}$ represents the maximum linguistic terms given in the scale.

Decomposed Fuzzy Analytic Hierarchy Process (DF-AHP)

The analytic hierarchy process (AHP) is one of the well-known multi-attribute decision-making (MADM) methods. It was presented by Saaty (1977). AHP is a technique that can be used to both weight attributes and select the most suitable alternative (Ebrahimi et al., 2015; Khajavi & Fattahi Nafchi, 2015). It can handle a wide range of decision-making problems, including both qualitative and quantitative factors (Moslem, 2024). This method structures a decision-making problem hierarchically, with the main goal at the top, the alternatives at the bottom, and the attributes on which the alternatives can be evaluated in the middle (Saaty, 1977).

To address uncertainty, fuzzy extensions of the AHP method have been used in various applications. Despite the popularity of fuzzy AHP extensions, existing methods fail to handle both positive and negative responses from decision-makers properly. In classical AHP, the reciprocal question is never asked directly; instead, the multiplicative inverse of the first answer is used, which can lose important information about the decision-maker's inconsistency. DFS solves this problem by incorporating both optimistic (positive) and pessimistic (negative) viewpoints, along with a consistency rate. Combining AHP with DFS makes pairwise comparisons more reliable by capturing the decision-maker's actual responses to both direct and reciprocal questions under uncertainty. As a result, DF-AHP is superior to classical AHP in complex problems like selecting a supplier in the pharmaceutical industry (Cebi et al., 2023), evaluating the food supply chain (Arslan et al., 2023), selecting transport companies (Arslan & Cebi, 2024), and selecting parcel locker location (Moslem et al., 2024). In the present study, the DF-AHP method was used to determine the weights of barriers to CSA adoption among farmers, and the method's steps are described below (Cebi et al., 2023).

Step one. Defining a decision problem: In this step, experts and evaluation attributes are defined.

Step two. Doing pairwise comparisons: To do pairwise comparisons, a pairwise matrix is initially constructed for each group of attributes. Then, experts are asked to compare the attributes using linguistic terms defined in Table 3 for both optimistic and pessimistic viewpoints.

Table 3. Linguistic scale for DF-ANP (Arslan & Cebi, 2024)

Optimistic linguistic terms	M	Θ	Saaty Scale	Pessimistic linguistic terms	μ	ϑ
Exactly Equal Importance (EEI)	0.50	0.50	1	Exactly Equal Unimportant (EEU)	0.50	0.50
Slightly More Important (SMI)	0.55	0.45	2	Slightly Equal Unimportant (SEU)	0.45	0.55
Weakly More Important (WMI)	0.60	0.40	3	Weakly More Unimportant (WMU)	0.40	0.60
More Important (MI)	0.65	0.35	4	More Unimportant (MU)	0.35	0.65
Strongly More Important (StMI)	0.70	0.30	5	Strongly More Unimportant (SMU)	0.30	0.70
Very Strongly More Important (VSI)	0.75	0.25	6	Very Strongly More Unimportant (VSU)	0.25	0.75
Absolutely More Important (AMI)	0.80	0.20	7	Absolutely More Unimportant (AMU)	0.20	0.80
Perfectly More Important (PMI)	0.85	0.15	8	Perfectly More Unimportant (PMU)	0.15	0.85
Exactly More Important (EMI)	0.90	0.10	9	Exactly More Unimportant (EMU)	0.10	0.90

Step three. Analyzing consistency: In this step, linguistic terms are first converted into crisp numbers using Saaty's scale. Then, the consistency of all matrices is assessed using Eqs. (17) and (18).

$$CR = \frac{CI}{RI} \tag{17}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{18}$$

If the matrices do not meet the consistency ($CR > 0.1$), it is necessary to ask the experts to change their pairwise comparisons.

Step four. Calculating the weight of each attribute for each expert: In this case, the weight of each attribute is calculated separately from the pairwise comparison matrix for each expert. Thus, if there are k experts, k distinct weights will be obtained for each attribute. To calculate these weights, the DWGM method outlined in Eq. (12) is used.

Step five. Calculating local weights: The weights calculated in the previous step are aggregated to determine the local weight for each attribute as a decomposed fuzzy number. They are also aggregated using DWGM.

Step six. Defuzzing DFNs: After calculating the weights as decomposed fuzzy numbers, the SI is calculated using Eq. (14), and the local weights are converted into crisp numbers. If the sum of the SIs obtained for each group of attributes is not equal to 1, they must be normalized.

Results

After identifying the barriers to CSA implementation and categorizing them into the four constructs of UTAUT (see Figure 1), the barriers' weights were calculated using the DF-AHP. To use this method, a questionnaire was structured in which experts (farmers) were asked to make pairwise comparisons of the UTAUT constructs and the barriers associated with each, using both optimistic and pessimistic approaches. To consider the two approaches, questions were asked of farmers in both positive and negative forms. For example:

Positive question: To what extent is "performance expectancy" more important than "effort expectancy" in the adoption of CSA by a farmer?

Positive question: To what extent is "performance expectancy" more unimportant than "effort expectancy" in the adoption of CSA by a farmer?

The linguistic variables of Table 3 were used to make the comparisons. The following is an example of a pairwise comparison of four UTAUT constructs completed by expert 1 (Table 4). It should be noted that, due to the large volume of data generated throughout the different steps of the DF-AHP, only the calculations related to the constructs of UTAUT are presented in detail to illustrate the calculation procedure. For the remaining analyses, only the final results are reported.

Table 4. Pairwise comparison matrix of Expert 1 with linguistic terms for constructs of UTAUT

	EE		PE		FC		SI	
	$O(\mu_{ij}^o,\vartheta_{ij}^o)$	$P(\mu_{ij}^p,\vartheta_{ij}^p)$	$O(\mu_{ij}^o,\vartheta_{ij}^o)$	$P(\mu_{ij}^p,\vartheta_{ij}^p)$	$O(\mu_{ij}^o,\vartheta_{ij}^o)$	$P(\mu_{ij}^p,\vartheta_{ij}^p)$	$O(\mu_{ij}^o,\vartheta_{ij}^o)$	$P(\mu_{ij}^p,\vartheta_{ij}^p)$
PE	EEI	EEI	SEU	EEI	AMU	SEU	SMU	WMU
EE	SMI	EEI	EEI	EEI	AMU	SEU	WMU	SEU
FC	AMI	SMI	AMI	SMI	EEI	EEI	SMU	EEI
SI	StMI	WMI	WMI	SMI	SMU	EEI	EEI	EEI

After collecting expert opinions, the CR for the pairwise comparisons was calculated using the Saaty method. For this purpose, the linguistic variables were first converted to their corresponding crisp values. Then, using Eqs. (17) and (18), the CR of all comparisons was determined. Table 5 presents the details of the CR calculation for the pairwise comparison matrix of Expert 1 for the UTAUT constructs. Given that $CR = 0.08$, and it is less than 0.1, the consistency of the comparisons was confirmed. These calculations were performed for all pairwise comparisons made by all experts, and the consistency of all was confirmed (see Appendix A).

Table 5. CR Calculation details for Expert 1's judgments for constructs of UTAUT

	W	WSV	ICV	CI	CR
PE	0.055	0.23	4.2192147	0.07	0.08
EE	0.080	0.34	4.2192151		
FC	0.641	2.70	4.2192147		
SI	0.224	0.95	4.2192153		

After confirming the consistency of the pairwise comparisons, the linguistic variables were converted into their corresponding DFNs, and the pairwise comparison matrix was formed using DFNs. Table 6 presents an example of this matrix for the constructs of UTAUT (Due to the large amount of data, only the DFN pairwise comparison matrix for the constructs of UTAUT and barriers in each category for all experts is provided in Appendix B; for other cases, only the results are reported).

Table 6. Pairwise comparison matrix with DFNs based on Expert 1's judgments for constructs of UTAUT

	PE				**EE**				**FC**				**SI**			
	μ_{ij}^{o}	ϑ_{ij}^{o}	μ_{ij}^{p}	ϑ_{ij}^{p}	μ_{ij}^{o}	ϑ_{ij}^{o}	μ_{ij}^{p}	ϑ_{ij}^{p}	μ_{ij}^{o}	ϑ_{ij}^{o}	μ_{ij}^{p}	ϑ_{ij}^{p}	μ_{ij}^{o}	ϑ_{ij}^{o}	μ_{ij}^{p}	ϑ_{ij}^{p}
PE	0.50	0.50	0.50	0.50	0.45	0.55	0.50	0.50	0.20	0.80	0.45	0.55	0.30	0.70	0.40	0.60
EE	0.55	0.45	0.50	0.50	0.50	0.50	0.50	0.50	0.20	0.80	0.45	0.55	0.40	0.60	0.45	0.55
FC	0.80	0.20	0.55	0.45	0.80	0.20	0.55	0.45	0.50	0.50	0.50	0.50	0.70	0.30	0.50	0.50
SI	0.70	0.30	0.60	0.40	0.60	0.40	0.55	0.45	0.30	0.70	0.50	0.50	0.50	0.50	0.50	0.50

In the next step, the weight of the four constructs of UTAUT and the barriers categorized under them were calculated separately for each expert using Eq. (12). For example, the weight of PE using the opinions of Expert 1 (Table 6) was obtained as follows:

$$a_{PE} = 0.50^{0.25} + 0.45^{0.25} + 0.20^{0.25} + 0.30^{0.25} = 0.341$$

$$b_{PE} = 1 - \big((1 - 0.50) \times (1 - 0.55) \times (1 - 0.80) \times (1 - 0.70)\big) = 0.659$$

$$c_{PE} = \frac{0.50 \times 0.50 \times 0.45 \times 0.40}{(0.50^3 \times 0.25 \times (1 - 0.50) + 0.50^3 \times 0.25 \times (1 - 0.50) + 0.45^3 \times 0.25 \times (1 - 0.45) + 0.40^3 \times 0.25 \times (1 - 0.40) + (0.50 \times 0.50 \times 0.45 \times 0.40))} = 0.457$$

$$d_{PE} = \frac{0.25 \times (0.50 + 0.50 + 0.55 + 0.60)}{\left(0.25 \times 0.50 - \frac{0.50}{4}\right) + \left(0.25 \times 0.50 - \frac{0.50}{4}\right) + \left(0.25 \times 0.55 - \frac{0.55}{4}\right) + \left(0.25 \times 0.60 - \frac{0.60}{4}\right)} = 0.538$$

The weights of the constructs of UTAUT were calculated based on the pairwise comparisons of Expert 1, as given in Table 7 (the weights obtained for the constructs of UTAUT by the other experts are provided in Appendix C).

Table 7. Weight of constructs of UTAUT based on Expert 1's judgments

	a	b	c	d
PE	0.341	0.659	0.457	0.538
EE	0.385	0.615	0.473	0.525
FC	0.688	0.312	0.524	0.475
SI	0.501	0.499	0.535	0.463

Next, the weights of the constructs of UTAUT and each category of barriers, which were calculated separately for each expert (see Appendix C), were aggregated using the DWGM (Eq. (12)). Table 8 shows the aggregated weights of the constructs of UTAUT.

Table 8. Aggregated weights of constructs of UTAUT

	a	b	c	d
PE	0.313	0.687	0.618	0.379
EE	0.348	0.652	0.609	0.385
FC	0.689	0.311	0.312	0.558
SI	0.520	0.463	0.001	0.698

After the weights are calculated as DFNs, the SI should be computed in order to compare the weights. In other words, DFNs are defuzzified using the SI method. Consequently, the barriers can be ranked based on their SI values. To do that, first the CI and then the SI were calculated using Eq. (13) and Eq. (14). The calculations of $CI(\widetilde{w}_{PE})$ and $SI(\widetilde{w}_{PE})$ were presented as an example. Table 9 shows other calculated local weight constructs for UTAUT.

$$CI(\widetilde{w}_{PE}) = 1 - \sqrt{\frac{(0.341-0.538)^2+(0.659-0.457)^2+(1-0.341-0.659)^2+(1-0.457-0.538)^2}{2}} = 0.932$$

$$SI(\widetilde{w}_{PE}) = \frac{(0.341+0.659-0.457+0.538)\times 0.932}{2\times 0.9} = 0.394$$

Table 9. Local weight of constructs of UTAUT

	CI	SI	N-SI
PE	0.932	0.394	0.201
EE	0.959	0.414	0.211
FC	0.870	0.602	0.307
SI	0.590	0.550	0.281

The obtained SI values are the factor weights, but they are not normalized. By normalizing the SI, the local weights of the constructs of UTAUT and all the barriers were obtained. These weights are shown in Table 10.

Table 10. Local weights of constructs of UTAUT and barriers

	Local Weight	Barriers	Local Weight
PE	0.201	PE_1	0.329
		PE_2	0.340
		PE_3	0.331
EE	0.211	EE_1	0.361
		EE_2	0.409
		EE_3	0.230
FC	0.307	FC_1	0.255
		FC_2	0.275
		FC_3	0.256
		FC_4	0.213
SI	0.281	SI_1	0.143
		SI_2	0.171
		SI_3	0.191
		SI_4	0.216
		SI_5	0.129
		SI_6	0.149

According to Table 9, facilitating conditions are the most important constructs in UTAUT for CSA implementation. Furthermore, in performance expectancy, PE2 (trade-off among the three objectives of CSA), in effort expectancy, EE2 (immaturity of some technologies and lack of an implementation guideline), in facilitating conditions, FC2 (superficial knowledge and fragmented perception), and in social influence, SI4 (kinship network enforcement) are the most significant barriers to CSA implementation. Finally, by multiplying the UTAUT constructs' weights by their corresponding barriers, the global weights for all barriers will be obtained (Table 11).

Table 11. Global weights of barriers

Barriers	Global Weight	Rank
PE_1	0.066	8
PE_2	0.068	6
PE_3	0.067	7
EE_1	0.076	5
EE_2	0.086	1
EE_3	0.049	11
FC_1	0.078	4
FC_2	0.085	2
FC_3	0.079	3
FC_4	0.066	8
SI_1	0.040	14
SI_2	0.048	12
SI_3	0.054	10
SI_4	0.061	9
SI_5	0.036	15
SI_6	0.042	13

Sensitivity Analysis

Sensitivity analysis is a crucial phase of MADM. Sensitivity analysis is done to determine the impact of changes in the input parameters on the output. The most commonly applied method of sensitivity analysis is adapting the attribute weight. If the results are unchanged after doing that, then it is said to be robust. Sensitivity analysis can also help in determining the attributes having significant impacts on the outcome (Demir et al., 2024; Parkouhi et al., 2025). In this study, two sensitivity analyses were conducted. The first sensitivity analysis examined the effect of expert weights on the overall barrier weights. In the aggregation of the weights calculated based on experts' judgments, the λ_i parameter is used. This parameter represents the importance assigned to each expert. It is usually set equal to $\frac{1}{n}$, meaning that all experts receive the same level of importance (Arslan et al., 2023; Cebi et al., 2023; Moslem et al., 2024). The barrier weights in this study were also calculated using this approach. According to the expert information presented in Table 2, Experts 4 and 6 have more work experience than the other experts. Therefore, they may provide more accurate judgments. In addition, both experts have academic backgrounds in agricultural management. In studies of technology adoption in agriculture, management knowledge can be valuable as well as agricultural knowledge. Therefore, Scenario 1 (S1) was defined by assigning double weight to Experts 4 and 6 (each with a weight of 0.25, while the remaining experts had a weight of 0.125). After recalculating the barrier weights, the new weights were obtained as shown in Table 12. It should be noted that Scenario 0 (S0) represents the original overall weights before any changes were made.

Table 12. Weights and ranks of barriers for S0 and S_1

Barriers	S_0	Rank S_0	S_1	Rank S_1
PE_1	0.066	8	0.067	7
PE_2	0.068	6	0.070	6
PE_3	0.067	7	0.066	9
EE_1	0.076	5	0.078	4
EE_2	0.086	1	0.085	1
EE_3	0.049	11	0.049	13
FC_1	0.078	4	0.076	5
FC_2	0.085	2	0.084	2
FC_3	0.079	3	0.079	3
FC_4	0.066	8	0.066	8
SI_1	0.040	14	0.040	14
SI_2	0.048	12	0.050	12
SI_3	0.054	10	0.054	11
SI_4	0.061	9	0.063	10
SI_5	0.036	15	0.034	16
SI_6	0.042	13	0.039	15

As shown in Table 12, the final weights changed only slightly, and the ranking of the barriers remained unchanged. To examine the relationship between the weights obtained under Scenarios S0 and S1, Kendall's coefficient was calculated. The results are presented below (Table 13).

Table 13. Sensitivity analysis results based on Kendall's rank correlation coefficient for S_1

Scenario	Kendall's Tau-b (τb)	sig. (2-tailed)
S_1	0.912	0.001

Table 13 shows a very strong positive relationship between the barriers' weights obtained under S0 and S1. This result indicates that these changes had a limited effect on the overall weighting pattern. Hence. this point confirms the robustness of the DF-AHP. In the second sensitivity analysis, the barrier weights were systematically adapted by a fixed percentage. This approach is widely used in previous MADM studies to test the robustness of models (Demir et al., 2024). In this analysis, six scenarios (Scenarios 2–7) were defined. In each scenario, the weights of the three most important barriers, the three least important barriers, or both groups were adapted by a fixed percentage. In scenario 2 (S2), there was a decrease of 10% in weight in the case of the three most important barriers. The weights of all the barriers were normalized. In scenario 3 (S3), there was an increase of 10% in weight in the case of the three least important barriers. In scenario 4 (S4), both reductions and increases took place simultaneously (There was a decrease of 10% in weight in the case of the three most important barriers, and there was an increase of 10% in weight in the case of the three least important barriers). In scenarios 5, 6, and 7 (S5, S6, S7), the same reductions and increases took place using 20%.

Table 14. The weights for all scenarios

Barriers	S_0	Rank S_0	S_2	Rank S_2	S_3	Rank S_3	S_4	Rank S_4	S_5	Rank S_5	S_6	Rank S_6	S_7	Rank S_7
PE_1	0.066	8	0.068	8	0.065	8	0.067	8	0.069	7	0.063	8	0.068	7
PE_2	0.068	6	0.070	6	0.067	6	0.069	6	0.072	4	0.065	6	0.070	4
PE_3	0.067	7	0.069	7	0.066	7	0.068	7	0.070	6	0.064	7	0.069	6
EE_1	0.076	5	0.078	4	0.075	5	0.077	4	0.080	2	0.073	5	0.078	2
EE_2	0.086	1	0.079	2	0.085	1	0.078	2	0.072	3	0.083	1	0.071	3
EE_3	0.049	11	0.050	12	0.048	12	0.050	12	0.052	12	0.047	14	0.050	13
FC_1	0.078	4	0.080	1	0.077	4	0.079	1	0.082	1	0.075	4	0.080	1
FC_2	0.085	2	0.078	3	0.084	2	0.077	3	0.072	4	0.082	2	0.070	4
FC_3	0.079	3	0.073	5	0.078	3	0.072	5	0.066	9	0.076	3	0.065	9
FC_4	0.066	8	0.068	8	0.065	8	0.067	8	0.069	7	0.063	8	0.068	7
SI_1	0.040	14	0.041	15	0.043	15	0.045	15	0.042	15	0.046	15	0.049	14
SI_2	0.048	12	0.049	13	0.047	13	0.049	13	0.050	13	0.046	15	0.049	14
SI_3	0.054	10	0.055	11	0.053	11	0.055	11	0.057	11	0.052	12	0.055	11
SI_4	0.061	9	0.063	10	0.060	10	0.062	10	0.064	10	0.059	10	0.063	10
SI_5	0.036	15	0.037	16	0.039	16	0.040	16	0.038	16	0.058	11	0.044	16
SI_6	0.042	13	0.043	14	0.046	14	0.047	14	0.044	14	0.048	13	0.052	12

Based on Kendall’s correlation coefficient, there is a very strong correlation between the rank of each scenario and the basic scenario (S0). The results of these analyses are shown in Table 15.

Table 15. Sensitivity analysis results based on Kendall’s correlation coefficient for S_2 to S_7

Scenario	Kendall’s correlation coefficient	sig. (2-tailed)
S_2	0.933	0.001
S_3	1	0.000
S_4	0.933	0.001
S_5	0.827	0.001
S_6	0.940	0.001
S_7	0.875	0.001

Discussion

The adoption of emerging approaches such as CSA by farmers (users) in developing countries like Iran faces fundamental barriers, which this research has analyzed. To ensure comprehensiveness, UTAUT, a user technology adoption model, was employed. UTAUT examines a more reasonable scenario in the context of technology adoption. This model incorporates the impact of technology-task fit, social influences, and resource availability (facilitating conditions) on individual behavior. Hence, this model has better explanatory power than other models and theories (Dissanayake et al., 2022). Among the four constructs of UTAUT, facilitating conditions and social influence were identified as more important than the others in Iran. Iran is a developing country, and the results of this study have been shaped in alignment with its political, economic, and cultural conditions. The greater significance of facilitating conditions in the adoption of CSA in Iran is due to the fact that, in developing countries, even basic infrastructure is not provided. These shortages create strong discouragement among farmers. In contrast, in developed countries, all facilitating conditions are already available, and these factors drive the implementation of CSA (Queiro et al., 2019). Furthermore, in Iran, due to cultural conditions and the greater influence of colleagues' and family members' opinions on decision-making, social influence is also important. In cultures with higher power distance and greater collectivism (low individualism), social norms have a stronger impact on users' behavioral intentions. In such societies, individuals' decisions rely more on the opinions and expectations of others (e.g., family, colleagues, and superiors) than on their own personal preferences (Im et al., 2011). Queiroz and Wamba (2019) confirm this finding in their study of blockchain adoption in agriculture across two countries, India and the United States. A notable point is that culture plays a significant role in the adoption and diffusion of technology, and UTAUT is a comprehensive model that can be applied across diverse cultures (Im et al., 2011).

Among the barriers, the “immaturity of some technologies and the lack of an implementation guideline” (EF2) were identified as the most significant barriers. One reason for this barrier is that research and development (R&D) and policies do not align with farm realities. Farmers emphasized that policy-making and research are often conducted away from the farm. In other words, many of the everyday realities that farmers face are overlooked. Consequently, this implies that the developed technologies do not meet farmers' desires or needs (Long et al., 2016). Furthermore, technological immaturity expresses a strong dependence on local conditions (climate, soil, topography), and this fact causes CSA to be efficient in some regions but fail in others. The lack of an implementation guideline appears in the form of a lack of standardized services, insufficient operator training, ambiguous contracts, and the absence of accountability mechanisms. Hence, they lead to the incomplete implementation of the CSA (Wang et al., 2025). EE2 is a fundamental constraint, and addressing it can facilitate reducing other barriers, such as “cognitive biases” and “lack of sufficient skills among farmers”. This is because clear guidelines and implementation procedures explain how CSA should be implemented. They clarify the knowledge and skills required for successful adoption and make it easier to identify training needs. They also improve farmers’ understanding of CSA and its benefits. As a result, they reduce uncertainty and misconceptions about its implementation. “Superficial knowledge and fragmented perception” (FC2) is the second most important barrier to CSA adoption in Mazandaran. Awareness is the foundation of behavioral change in agricultural systems. Illiteracy and lack of knowledge make it difficult for farmers to interpret advisory messages, understand CSA technologies, or participate in extension-based capacity-building. Therefore, illiteracy indirectly intensifies the effects of other barriers by limiting access to enabling resources (Saikia et al., 2025). Saikia et al. (2025) also identified this barrier as one of the most Important.

“Time-consuming practices” and “difficulty in monitoring CSA outcomes” are two barriers that can be alleviated by reducing FC2. Greater awareness helps farmers better understand the long-term benefits of CSA practices, making them more willing to accept the time and effort these practices require. In addition, a more comprehensive understanding of CSA enables farmers to make better decisions, lowers their perceived economic risk, and improves their ability to monitor the outcomes of CSA implementation. As seen in the research findings, “high implementation costs and economic risk” is the third important barrier to the adoption of CSA by farmers in Iran (Mazandaran). Long et al. (2016), while emphasizing the importance of costs in CSA adoption, noted that farmers' sensitivity to costs can vary across regions. For example, farmers in Switzerland face tremendous cost pressures compared to other markets. Labor and input costs are high in Switzerland. Additionally, investment costs are high because this country has many small and medium-sized farms that largely lack the financial capacity to invest (Long et al., 2016). Due to its political and economic conditions and the boycott Iran faces, it is also among the regions where the cost of implementing CSA is high and constitutes a major barrier.

Mishra et al. (2026) in India and Lenhardt et al. (2026) in Kenya, both developing countries, also identified cost as the most important barrier. Lenhardt et al. (2026) stated in their study that farmers are generally not from wealthy backgrounds. They must first obtain financial resources through other means to acquire the basic tools for cultivating their own land. For example, farmers must first work on their neighbors' land and then use the money they earn to invest in farming their own land. Therefore, under such conditions, they cannot think about changing their agricultural system. In Iran, farmers are generally not from wealthy backgrounds, and similar conditions prevail. Reducing FC3 can also decrease the impact of other barriers, such as “kinship network enforcement” and “farmers' lack of access to resources and technology”. Farmers typically operate within family-based farming systems and generally belong to the middle-income segment of society. Providing financial resources can reduce family members' resistance to implementing changes, such as adopting CSA. Moreover, the provision of the infrastructure, facilities, and equipment required for CSA implementation depends on securing financial support. In the initial steps to reduce barriers to CSA adoption among farmers, corrective actions can be taken. According to experts at Iran's Ministry of Agriculture Jihad, strengthening farmers' social participation is one of the most important policy strategies for climate change adaptation (Dehghanpour et al., 2020). Technology providers should involve end users (farmers) from the beginning in the design and development process. This ensures the technology is designed to meet the farm's needs and realities, reducing issues such as overly complex scientific language or a lack of alignment with actual conditions.

Furthermore, these experts have identified diversifying farmers' income sources as another key strategy for climate change adaptation. By strengthening farmers' economic resilience and providing additional financial resources, income diversification can help offset the initial investment costs associated with implementing CSA practices. Hence, this strategy facilitates farmers’ adoption and long-term sustainability (Dehghanpour et al., 2020). Since much of the economic benefit of CSA lies with food manufacturing and retailers, while the costs fall on farmers, policies should be established to ensure that benefits also flow toward farmers. For example, companies can address this imbalance by investing in CSA technologies on their supply farms. Additionally, government subsidies for improved seeds can make prices more affordable for farmers. Establishing training programs for farmers is another action that decision-makers can consider. These trainings should be delivered in simple language, free from specialized and complex terminology. This course may be suitable for farmers with limited literacy and knowledge. For instance, instead of talking about “climate change,” one could speak of “changes in the growing season,” a term more familiar to farmers (Heydari & Morid, 2020).

Conclusion

Climate change is a very important issue that has brought many people from around the world into a state of alarm in recent times. Food security is an issue that arises as the population increases, and climate change will further increase its significance. They become very crucial issues for developing nations like Iran because of the importance of agriculture in their economy. One way to address these challenges is to adopt CSA. Despite the positive impacts of CSA, some barriers prevent its adoption by farmers. In this study, the barriers to CSA adoption among farmers in Mazandaran, which accounts for a large share of Iran's agricultural output, were identified. The identified barriers were then classified under the four constructs of the UTAUT. This classification helps to determine how the barriers influence farmers' behavioral intention. Also, it helps identify strategies and actions to address barriers more effectively. Furthermore, this study calculated the importance of these barriers using the DF-AHP method. Using this method covers the incomplete information of experts and environmental uncertainty, and produces more valid results. Given the importance of CSA in recent years, researchers are advised to consider the following gaps in future research:

- In this study, barriers affecting farmers' adoption have been examined. Researchers can assess adoption at the organizational level. In this investigation, they can use theories such as the Technological-Organizational-Environmental (TOE) framework, which evaluates technology adoption in organizations.
- Reducing the barriers to CSA adoption by farmers requires corrective actions. Researchers can use the findings of this study to develop strategies for each of the four barrier groups.
- In calculating barrier weights, other approaches, such as grey, Pythagorean fuzzy, and spherical fuzzy, can be used under uncertain conditions and compared with each other.
- In this study, the weight of barriers to CSA adoption from the farmers' perspective has been calculated. Researchers can examine the relationships between these barriers in their research using methods such as ISM.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors declare compliance with all applicable ethical guidelines, including proper data handling, originality of content, and avoidance of duplicate submission.

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Conflict of interest

The authors declare no conflict of interest.

Appendix A, B and C. Supplementary data

Supplementary material related to this article can be found online at
https://cdn.imgurl.ir/uploads/l121578_Appendix_A_B_and_C._Supementary_data.docx

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