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# Farmers' Behavioral Intention to Adopt Agrovoltaic Systems in Semi-Arid Iran: Findings from Structural Equation Modeling and Fuzzy-Set Qualitative Comparative Analysis

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**Abstract**

Water scarcity and energy insecurity threaten sustainable agriculture in semi-arid regions such as Iran, underscoring the need for innovations like agrovoltaic (AV) systems. This study was conducted in Fariman County, a water-stressed agricultural region in northeastern Iran, and investigates the determinants of Iranian farmers' behavioral intention to adopt AV technology based on survey data collected from 215 large-scale irrigated farmers using a face-to-face questionnaire. The study employs a mixed-method approach that integrates Structural Equation Modeling (SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA). Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the study examines key behavioral and contextual factors influencing farmers' behavioral intentions to adopt Agrovoltaic systems. SEM results indicate that perceived benefits, ease-of-use considerations, and social influences significantly shape behavioral intentions, explaining a substantial proportion of variance in behavioral intention ($R^2$ =0.58), while risk perceptions weaken the impact of perceived benefits. fsQCA identifies three alternative pathways leading to high behavioral intention, all characterized by low perceived risk and strong social influence. The findings emphasize that psychological and social factors are as critical as technical and economic ones. Policy efforts should therefore focus on reducing perceived risks and leveraging social networks to accelerate AV adoption in water-stressed agriculture.

**Keywords:** Agrivoltaics, Farmer decision-making, Risk perception, Solar-based agricultural innovations, Technology acceptance.

## 1. Introduction

Water scarcity and energy constraints have become defining pressures on agricultural production in arid and semi-arid regions, particularly in countries such as Iran where agriculture is the dominant water user and irrigation practices are highly energy-dependent (Ashraf et al., 2021).

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These challenges directly affect farm productivity, resource sustainability, and the economic viability of rural livelihoods. In this context, agrovoltaic (AV) systems offer a dual-use land approach that can simultaneously enhance water-use efficiency, reduce diesel consumption, and provide on-farm renewable energy for irrigation and other agricultural operations. These characteristics position AV systems as a technologically relevant option for improving agricultural resilience under intensifying water and energy stress (Toledo & Scognamiglio, 2021). Recent field-based evidence from a dynamic agrivoltaic system shows that partial panel shading can reduce crop evapotranspiration by about 13%, while consistently shaded areas may achieve reductions of up to 81% compared with full-sun conditions, highlighting the strong water-saving potential of agrivoltaics in arid and semi-arid agriculture (Disciglio et al., 2025).

Iran faces one of the most acute water crises globally, characterized by rapid declines in groundwater levels, deteriorating water quality, and extremely low irrigation efficiency. The agricultural sector consumes more than 90% of national freshwater resources yet remains vulnerable to outdated irrigation technologies, climate variability, and rising production costs. At the same time, the national energy system experiences growing electricity demand, periodic power shortages, and persistent reliance on fossil fuels, while decentralized renewable energy technologies—particularly those tailored to rural contexts—remain underutilized. These interlinked pressures highlight the need for integrated water–energy solutions for Iranian agriculture (Saemian et al., 2022).

Agrovoltaic systems represent a promising pathway toward such integration by allowing simultaneous crop cultivation and solar power generation on the same land. International evidence from Germany, Japan, India, and other countries demonstrates that AV systems can improve land productivity, reduce evapotranspiration, strengthen energy security, and diversify farm income (Barron-Gafford et al., 2019; Mehta et al., 2025). However, adoption outcomes vary considerably depending on agro-climatic conditions, policy support mechanisms, and farmers' behavioral responses (Ashraf et al., 2021). In Iran, despite a few pilot-scale initiatives and recent incentives introduced by the Renewable Energy and Energy Efficiency Organization (SATBA) _ including feed-in tariffs and small-scale power purchase agreements_ the economic rationale for agrivoltaic adoption is not primarily based on electricity sales to the grid, but rather on on-farm energy self-consumption and indirect benefits related to water-use efficiency and cost reduction. As a result, AV systems remain underdeveloped, and empirical research on farmers' adoption decision-making is highly limited. (Abbaspour et al., 2007; Khalilpour & Vassallo, 2015).

Among Iran's provinces, Khorasan Razavi is a major agricultural region severely affected by water scarcity and groundwater depletion. Over half of its 37 plains are critically overdrawn. The Fariman plain faces an annual groundwater deficit exceeding 80 million cubic meters, with land subsidence between 120 and 180 millimeters per year. The Fariman dam holds less than 19% of its designed capacity, seriously limiting irrigation and crop yields. Given these conditions, water- and energy-saving technologies that are both technically feasible and socially acceptable are urgently needed. However, agrovoltaic adoption depends not only on technical or economic factors but also on behavioral dimensions such as perceived usefulness, perceived risk, and social influence (Haghshenas Haghighi & Motagh, 2024).

Despite growing global attention to agrivoltaics, significant gaps remain in understanding the behavioral factors that shape farmers' willingness to adopt these systems under conditions of severe water and energy stress. While prior research in Iran has applied the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine rural households' general intention to use renewable energy sources, such studies have primarily relied on linear, variance-based approaches and have not focused on agrivoltaic technologies or agricultural decision-making contexts. Moreover, previous studies have rarely examined the role of perceived risk or employed integrated analytical frameworks that combine linear and configurational approaches.

To address these gaps, the present study applies a mixed-method framework incorporating Structural Equation Modeling (SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) to (i) identify key determinants of farmers' behavioral intention, (ii) examine the moderating effect of perceived risk, and (iii) uncover multiple configurational pathways that may lead to high adoption behavioral intention. This study makes an original contribution by moving beyond purely linear analyses and introducing a combined SEM–fsQCA approach to reveal both net effects and multiple, equifinal adoption pathways, thereby offering a more nuanced understanding of farmers' decision-making under water and energy constraints. The research is guided by the following objectives:

- To examine the effects of UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) on farmers' behavioral intention to adopt agrovoltaic systems in Fariman county.

- To analyze the direct and moderating role of perceived risk in shaping farmers' behavioral intention.
- To identify alternative configurational pathways leading to high behavioral intention using fsQCA.

## 2. Literature Review

Understanding how farmers adopt new technologies under uncertainty has long been a central theme in agricultural innovation research. Earlier studies frequently relied on Rogers' Diffusion of Innovations Theory (Rogers, 2003), emphasizing perceived relative advantage, complexity, and observability in shaping adoption decision. Alongside diffusion-based perspectives, individual-level behavioral models such as the Technology Acceptance Model (TAM) (Davis, 1989a) and the Theory of Planned Behavior (TPB) (Ajzen, 1991) have been widely applied to explain technology adoption through perceived usefulness, ease of use, attitudes, subjective norms, and perceived behavioral control. However, these models have been criticized for their limited ability to capture contextual constraints, risk perceptions, and institutional conditions that characterize agricultural decision-making under uncertainty. More recent work therefore integrates broader behavioral and psychological constructs—such as risk perception, trust, and environmental attitudes (Momani, 2020; Venkatesh et al., 2012b)— to better explain decision-making under climate and resource stress. In water-scarce regions like the Middle East and North Africa (MENA), conservative farming practices, limited extension access, and institutional mistrust hinder the uptake of clean technologies (Leiserowitz, 2006). Consequently, farmer-centered analytical approaches that integrate behavioral, contextual, and institutional dimensions are increasingly viewed as essential for diffusing renewable energy technologies in agriculture (El Bilali & Allahyari, 2018).

Agrovoltaic systems, which enable simultaneous crop cultivation and solar power generation, have been tested across diverse socio-ecological settings. Evidence from Europe, the United States, and Asia shows improvements in water-use efficiency, shading benefits, and additional income streams (Amaducci, 2018; Barron-Gafford et al., 2019) Yet, technical success alone rarely ensures widespread adoption. Factors such as land tenure, training, and financial incentives have driven adoption in India (Mahto et al., 2021),while trust in service providers was key in Bangladesh (Pahlavan et al., 2022), and awareness and demonstrated productivity gains supported uptake of solar drip irrigation in Sub-Saharan Africa (Maia et al., 2021). In Iran, agrovoltaic applications remain largely experimental, with limited deployment of solar-based agricultural energy systems. Although some studies have assessed the technical potential of solar technologies in agriculture(Ghasemi et al., 2019), behavioral aspects of adoption—especially within structured theoretical frameworks—remain unexplored.

Overall, the existing literature shows that while agronomic and technical factors are important, they do not fully explain farmers' adoption of agrovoltaic systems under uncertainty and resource stress. Behavioral constructs—such as perceived usefulness, ease of use, social influence, and perceived risk—play a critical role, yet they have rarely been examined within a unified theoretical framework. Moreover, studies in Iran have focused primarily on technical feasibility, offering limited insight into farmers' psychological drivers or contextual barriers. These gaps highlight the need for a theory-driven approach. Compared to single-theory models such as TAM [2]or Diffusion of Innovations, UTAUT offers a more comprehensive framework by integrating performance-related, effort-related, social, and facilitating dimensions within a unified structure. This integrative nature makes UTAUT particularly suitable for analyzing complex adoption decisions in agriculture, where technological uncertainty, social influence, and institutional constraints interact simultaneously.

The UTAUT framework aligns closely with determinants identified in prior studies, but it has not been applied to AV adoption in Iran. This study addresses these gaps by employing UTAUT and exploring both linear and configurational pathways of adoption.

## 3. Theoretical Framework and Hypothesis Development

To examine the behavioral aspects of agrovoltaic adoption, this study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by (Venkatesh et al., 2003) . UTAUT was selected because it captures both individual perceptions and contextual influences, which are critical in explaining farmers' adoption behavior under conditions of financial risk and technological uncertainty. UTAUT synthesizes eight earlier technology adoption models and identifies four core constructs as direct determinants of Behavioral Intention (BI): Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).

[2] . Technology Acceptance Model

In agricultural settings, these constructs reflect farmers' expectations of agronomic and financial gains (PE), ease of learning and use (EE), social support from peers and institutions (SI), and access to enabling resources such as training or credit (FC).

Given the financial uncertainty and technical unfamiliarity surrounding agrovoltaic systems, Perceived Risk (PR) is incorporated as an additional construct. Drawing on renewable energy and rural innovation studies (Bhatnagr & Rajesh, 2024) , PR is hypothesized to directly affect BI and moderate the effects of the four UTAUT predictors.

These four constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—constitute the core determinants of behavioral intention to adopt new technologies (Venkatesh et al., 2003a). In agricultural and renewable energy contexts, these constructs capture farmers' expectations regarding performance and economic benefits, perceived ease of use, social encouragement from relevant actors, and the availability of institutional and technical support. Prior studies applying UTAUT in rural and agricultural settings have confirmed the relevance of these factors in explaining farmers' adoption intentions toward innovative energy and farming technologies (Rezaei & Ghofranfarid, 2018). In addition, perceived risk reflects farmers' concerns about financial loss, technical uncertainty, and potential negative impacts on agricultural production. In technology adoption under conditions of uncertainty, higher perceived risk has been shown to reduce behavioral intention and to condition the effects of perceived benefits, ease of use, social influence, and facilitating conditions on adoption decisions (Momani, 2020; Venkatesh et al., 2012a).

Accordingly, the following hypotheses are proposed:

- **H1**: Performance Expectancy positively influences farmers' behavioral intention to adopt agrovoltaic systems.
- **H2**: Effort Expectancy positively influences farmers' behavioral intention to adopt agrovoltaic systems.
- **H3**: Social Influence positively influences farmers' behavioral intention to adopt agrovoltaic systems.
- **H4**: Facilitating Conditions positively influence farmers' behavioral intention to adopt agrovoltaic systems.
- **H5**: Perceived Risk negatively influences farmers' behavioral intention to adopt agrovoltaic systems.

- **H6**: Perceived Risk moderates the relationships between (a) Performance Expectancy, (b) Effort Expectancy, (c) Social Influence, and (d) Facilitating Conditions and Behavioral Intention.

Based on these constructs and hypotheses, the conceptual framework guiding this study is illustrated in Figure 1.

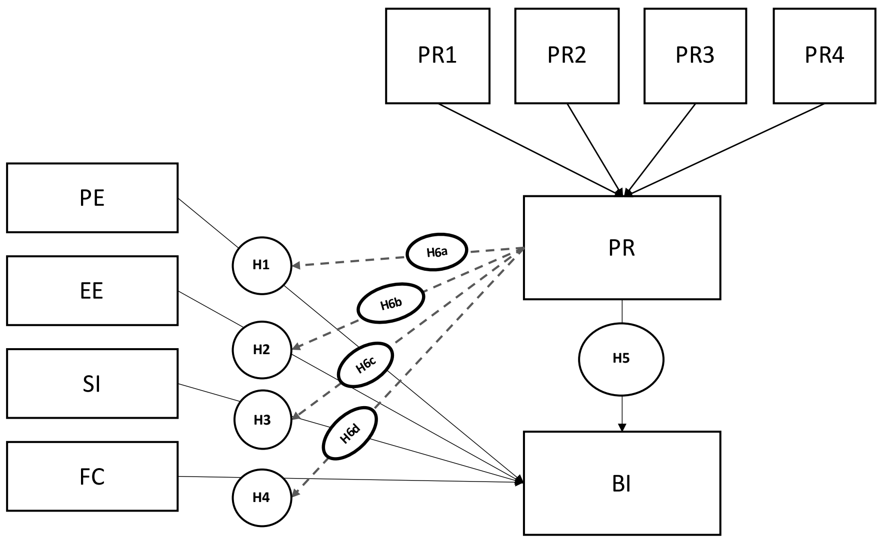


Figure 1. Conceptual model for farmers' behavioral intention to adopt agrovoltaic systems based on the UTAUT framework.

Figure 1 summarizes the proposed conceptual framework examined in this study. This framework underpins the empirical analysis using Partial Least Squares SEM and fuzzy-set QCA, highlighting the methodological contribution of the study by enabling the exploration of both linear and configurational pathways of agrovoltaic adoption in semi-arid Iran.

## 4. Methodology

### 4.1. Study Area

Fariman County, in southeastern Razavi Khorasan Province, northeastern Iran (Figure 2), lies within a semi-arid zone characterized by lower rainfall than the provincial average, with an annual precipitation of approximately 103 mm during the period 1400–1402. Agriculture is the main economic activity, relying largely on groundwater under arid conditions. Given the documented groundwater depletion in Razavi Khorasan Province (Iran Water Resources Management

Company, 2018), Fariman represents a water-stressed agricultural context suitable for examining behavioral factors influencing agrovoltaic adoption.

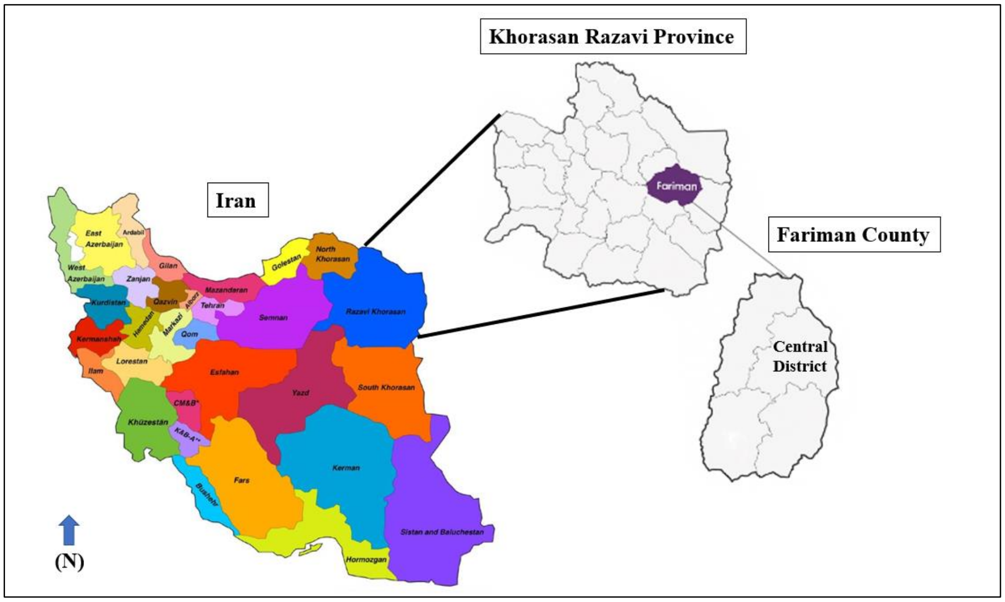


**Figure 2.** Geographic location of Fariman County within Razavi Khorasan Province, Iran. Source: Author's own elaboration using administrative map data.

### 4.2. Sampling Procedure and Data Collection

Given the substantial capital and operational demands of agrovoltaic systems, this study targeted large-scale farmers managing ≥5 hectares of cultivated land—consistent with national classifications and prior adoption studies in Iran (Amghani et al., 2025). A purposive sample of 215 farmers was drawn from the Central District of Fariman County, where irrigated agriculture and electricity access are concentrated. Selection was based on land size, active irrigation farming, and accessibility for interviews. Data were collected through face-to-face questionnaires administered by trained enumerators between April and May 2025. The sample satisfies statistical requirements for PLS-SEM (Hair et al., 2019a), and ensures adequate configurational depth for fsQCA (Ragin, 2008). However, as purposive sampling was used, the generalizability of the findings beyond the study context may be limited.

### 4.3. Variables and Measurement

The constructs and measurement items were derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), supplemented with empirical evidence from studies on agricultural innovation and renewable energy adoption in developing countries.

All items were rated on a five-point Likert scale (1 = “Strongly disagree” to 5 = “Strongly agree”), unless stated otherwise.

- **Performance Expectancy (PE)**: The extent to which farmers believe agrovoltaic systems can enhance productivity, reduce input costs, and generate additional income (e.g., electricity sales).
- **Effort Expectancy (EE)**: The perceived ease of understanding, learning, and using agrovoltaic systems, reflecting cognitive simplicity and usability (Davis, 1989; Venkatesh et al., 2012).
- **Social Influence (SI)**: The perceived encouragement or pressure from family, peers, cooperatives, or extension agents to adopt agrovoltaics (Rezaei-Moghaddam & Salehi, 2010).
- **Facilitating Conditions (FC)**: The availability of enabling infrastructure such as financial access, technical training, institutional backing, and extension services(Venkatesh et al., 2003).
- **Perceived Risk (PR)**: Farmers’ concerns about financial loss, technical uncertainty, or negative yield impacts. Indicators capture high investment cost (PR1), doubts about long-term performance (PR2), potential shading effects (PR3), and maintenance complexity (PR4) (Dwivedi et al., 2019; Kumar et al., 2023).
- **Behavioral Intention (BI)**: The likelihood of adopting agrovoltaic systems, assessed through standard measures of willingness and intention (Venkatesh et al., 2012).

All constructs were reflective and measured with multiple indicators. A pilot test with 10 local farmers refined the questionnaire to ensure clarity, contextual relevance, and face validity (Johanson & Brooks, 2010; Presser et al., 2004) .The finalized measurement items are listed in Appendix A.

### 4.4. Data Analysis Strategy

To examine the factors influencing farmers’ adoption of agrovoltaic systems, this study employs a dual analytical approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA). These methods are complementary: PLS-SEM tests linear, symmetric relationships among latent constructs, whereas fsQCA uncovers causal complexity by identifying multiple, asymmetric pathways leading to the same outcome (Ragin, 2009; Woodside, 2013). Integrating both enables theory testing while revealing configurational conditions that foster agrovoltaic adoption. Table 1 summarizes the study variables, their conceptual definitions, and measurement characteristics used in both PLS-SEM and fsQCA analyses.

**Table 1.** Variables, descriptions, and measurement

| Variables | Description | Number of items and measurement scale |
|---|---|---|
| Performance Expectancy (PE) | Perceived benefits of agrovoltaic systems in terms of productivity enhancement, irrigation cost reduction, additional income generation, and climate-resilient farming (PE1–PE4). | 4 Items. 5-point Likert scale (1-5) |
| Effort Expectancy (EE) | Perceived ease of learning, understanding, and operating agrovoltaic systems (EE1–EE3) | 3 Items. 5-point Likert scale (1-5) |
| Social Influence (SI) | Perceived social pressure and encouragement from important others, peers, and extension agents to adopt agrovoltaic systems (SI1–SI3). | 3 Items. 5-point Likert scale (1-5) |
| Facilitating Conditions (FC) | Availability of financial resources, institutional support, and technical assistance for implementing agrovoltaic systems (FC1–FC3). | 3 Items. 5-point Likert scale (1-5) |
| Perceived Risk (PR) | Perceived financial, technical, and production-related risks associated with agrovoltaic adoption (PR1–PR4). | 4 Items. 5-point Likert scale (1-5) |
| Behavioral Intention (BI) | Intention and willingness to adopt and integrate agrovoltaic systems into farm operations (BI1–BI3). | 3 Items. 5-point Likert scale (1-5) |

#### 4.4.1. PLS-SEM Analysis:

Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted in SmartPLS 4.0, suitable for exploratory research involving complex models and moderate sample sizes (Hair et al., 2019b). The analysis proceeded in two stages: (1) Measurement model assessment, evaluating reliability and validity through Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and discriminant validity via the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratio; and (2) Structural model evaluation, estimating path coefficients, $R^2$, and predictive relevance ($Q^2$), with significance tested using bootstrapping of 5,000 subsamples.

#### 4.4.2. fsQCA Analysis:

To complement the SEM findings, fuzzy-set Qualitative Comparative Analysis (fsQCA) was employed as a set-theoretic approach that examines how different combinations of conditions jointly lead to an outcome, allowing for causal asymmetry and multiple alternative pathways. Accordingly, fsQCA was performed using fs/QCA 3.0. Likert-scale data were calibrated into fuzzy-set scores through the direct method with qualitative anchors for full membership (0.95), crossover (0.50), and full non-membership (0.05) (Ragin, 2009a). The procedure included: (1)

necessary condition analysis to identify predictors essential for high behavioral intention; (2) sufficiency analysis to determine combinations of causal factors (e.g., performance expectancy, social influence, perceived risk) leading to high or low behavioral intention; and (3) evaluation of consistency, coverage, and alternative solution pathways to capture diverse adoption patterns.

### 4.4.3. Sample Size Justification:

The final dataset included 215 valid responses from major landholders. This sample size satisfies the minimum thresholds for PLS-SEM based on the 10-times rule and power analysis (Hair et al., 2019a) .The fsQCA approach is also robust for medium-sized samples and has been effectively applied in studies with fewer than 200 cases(Ragin, 2009a). PLS-SEM and fsQCA analyses were conducted using SmartPLS 4.0 and fs/QCA 3.0, respectively—both widely used tools in social science and sustainability research.

## 5. Result

Table 2 summarizes respondents' demographics: the average age was about 50 years, with most having over 20 years of farming experience. The majority completed primary or secondary education, and more than half were cooperative members. Regarding income, the largest group (36.7%) reported monthly earnings between 10–15 million IRR.

**Table 2.** Demographic Characteristics of Respondents (n = 215)

| Quantitative Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Age (in years) | 49.56 | 12.12 | 30.0 | 69.0 |
| Farming experience (in years) | 22.47 | 10.02 | 5.0 | 39.0 |
| Landholding size (in hectares) | 19.93 | 4.65 | 8.0 | 35.0 |

| Categorical Variable | Categories | Percentage |
|---|---|---|
| Education level | Illiterate | 14.4 |
| | Primary | 47.4 |
| | Secondary | 25.1 |
| | University | 13.0 |
| Monthly income category (Million IRR) | < 5 million | 8.4 |
| | 5-10 million | 15.3 |
| | 10-15 million | 36.7 |
| | 15-20 million | 27.0 |
| | > 20 million | 12.6 |
| Cooperative membership status | Not member | 48.4 |
| | member | 51.6 |
| Previous experience with renewable energy or advanced agricultural technologies | No | 55.3 |
| | Yes | 44.7 |

### 5.1. PLS-SEM Results

To examine potential common method bias (CMB), Harman's single-factor test was performed using unrotated exploratory factor analysis (EFA) on all measurement items. The first factor explained 34.21% of the total variance—well below the 50% threshold—in (Fuller et al., 2016; Podsakoff et al., 2003a)dictating that common method variance was not a major concern (Podsakoff et al., 2003b). The results of this test are summarized in Table 3.

**Table 3.** Results of Harman's single-factor test.

| Factor | Eigenvalue | % Of Variance | Cumulative |
|---|---|---|---|
| 1 | 5.70 | 34.21% | 34.21% |
| 2 | 2.20 | 13.19% | 47.40% |
| 3 | 1.53 | 9.15% | 56.55% |
| 4 | 1.24 | 7.43% | 63.98% |
| 5 | 1.02 | 6.14% | 70.12% |
| 6 | 0.89 | 4.83% | 74.95% |

#### 5.1.1. Measurement Model Assessment

Reliability and convergent validity of the reflective measurement model were assessed using Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and indicator loadings. As shown in Table 4, all constructs showed strong internal consistency, with Cronbach's alpha and CR above 0.7 and AVE exceeding 0.5, confirming convergent validity. All factor loadings were acceptable except PE4 (Agrovoltaic systems are useful for climate-resilient farming), which had a loading of 0.62. It was retained for theoretical relevance, as removing it only slightly increased AVE (from 0.61 to 0.64). Detailed item loadings are provided in Appendix B.

**Table 4**. Construct reliability and internal consistency of measurement model.

| Construct | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| Performance Expectancy (PE) | 0.78 | 0.86 | 0.61 |
| Effort Expectancy (EE) | 0.76 | 0.84 | 0.59 |
| Social Influence (SI) | 0.74 | 0.83 | 0.56 |
| Facilitating Conditions (FC) | 0.71 | 0.82 | 0.55 |
| Perceived Risk (PR) | 0.79 | 0.87 | 0.62 |
| Behavioral Intention (BI) | 0.75 | 0.85 | 0.60 |

All constructs meet the recommended thresholds for internal consistency and convergent validity ($\alpha > 0.7$, CR > 0.7, AVE > 0.5) (Hair & Hult, 2017).

Discriminant validity was also assessed using the Fornell–Larcker criterion. As shown in Table 5, the square root of the average variance extracted (AVE) for each construct (diagonal values) was greater than its correlations with other constructs (off-diagonal values). This confirms that all constructs satisfy the criterion for discriminant validity (Fornell & Larcker, 1981).

**Table 5.** Discriminant validity assessment using the Fornell–Larcker criterion.

| | PE | EE | SI | FC | PR | BI |
|---|---|---|---|---|---|---|
| **PE** | **0.78** | | | | | |
| **EE** | 0.52 | **0.77** | | | | |
| **SI** | 0.54 | 0.52 | **0.75** | | | |
| **FC** | 0.56 | 0.54 | 0.52 | **0.74** | | |
| **PR** | 0.58 | 0.56 | 0.54 | 0.52 | **0.79** | |
| **BI** | 0.60 | 0.58 | 0.56 | 0.54 | 0.52 | **0.77** |

To further assess discriminant validity, the Heterotrait–Monotrait (HTMT) ratio of correlations was calculated. As shown in Table 6, all HTMT values were below the recommended threshold of 0.85 (Henseler et al., 2015), indicating adequate discriminant validity among constructs.

**Table 6.** Discriminant validity assessment using the HTMT criterion

| | PE | EE | SI | FC | PR | BI |
|---|---|---|---|---|---|---|
| **PE** | – | | | | | |
| **EE** | 0.57 | – | | | | |
| **SI** | 0.59 | 0.57 | – | | | |
| **FC** | 0.61 | 0.59 | 0.57 | – | | |
| **PR** | 0.63 | 0.61 | 0.59 | 0.57 | – | |
| **BI** | 0.65 | 0.63 | 0.61 | 0.59 | 0.57 | – |

### 5.1.2. Structural Model Evaluation

After validating the measurement model, the structural model was assessed to test the hypotheses using bootstrapping with 5,000 resamples *(Hair & Hult, 2017)*. As shown in Table 7, PE, SI, and PR significantly affected Behavioral Intention (BI), supporting H1, H3, and H5. EE had only a marginal effect ($\beta = 0.134$, $t = 1.743$, $p = 0.082$), with a 95% CI of –0.015 to 0.283, indicating weak significance. The non-significant role of Facilitating Conditions (FC) likely reflects limited or unreliable institutional and infrastructural support in Iran's semi-arid regions, where farmers often distrust or lack access to effective extension, training, or credit services.

**Table 7**. Results of the Structural Model Estimation (Direct Effects).

| Hypothesis | Path | Coefficient | t-value | P-value | Result |
|---|---|---|---|---|---|
| H1 | PE → BI | 0.263 | 2.791 | 0.005 | Supported |
| H2 | EE → BI | 0.134 | 1.743 | 0.082 | Marginally supported ($p < 0.10$) |
| H3 | SI → BI | 0.218 | 2.305 | 0.021 | Supported |
| H4 | FC → BI | 0.096 | 1.134 | 0.257 | Not Supported |
| H5 | PR → BI | -0.211 | 2.087 | 0.037 | Supported |

Additionally, the model's explanatory and predictive power were evaluated. The coefficient of determination ($R^2$) for Behavioral Intention (BI) was 0.58, indicating that the independent variables explain about 58% of its variance—reflecting a moderate to substantial level of explanatory strength (Chin, 1988). Predictive relevance was assessed using the blindfolding procedure, yielding a $Q^2$ value of 0.34, which exceeds the recommended threshold of 0.0 and confirms adequate predictive capability (Hair et al., 2019).

### 5.1.3. Moderating Effects

To examine the moderating role of Perceived Risk (PR), interaction terms were added to the structural model. As shown in Table 8, only the interaction between Performance Expectancy (PE) and PR was significant ($\beta = –0.174$, $p < 0.05$), supporting H6a. This suggests that higher perceived risk weakens the positive effect of PE on Behavioral Intention (BI), meaning that even when farmers expect productivity or income gains, risk concerns reduce adoption behavioral intention. The moderating effects of PR on Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) were insignificant, rejecting H6b–H6d and indicating that PR does not substantially modify the influence of ease of use, peer support, or institutional assistance on adoption decisions.

**Table 8**. Moderating Effects of Perceived Risk.

| Interaction Term | hypothesis | Coefficient | t-value | Moderation |
|---|---|---|---|---|
| PE × PR → BI | H6a | -0.174 | 2.014 | Significant |
| EE × PR → BI | H6b | -0.089 | 1.352 | NS[3] |
| SI × PR → BI | H6c | -0.072 | 1.098 | NS |
| FC × PR → BI | H6d | -0.081 | 1.204 | NS |

[3] . Not Significant

### 5.2. Analysis of data using fsQCA

To complement the linear relationships identified through PLS-SEM, fuzzy-set Qualitative Comparative Analysis (fsQCA) was employed to uncover alternative, non-linear configurations leading to high adoption behavioral intention. As a set-theoretic approach, fsQCA effectively identifies multiple sufficient pathways, particularly valuable in contexts characterized by behavioral complexity and uncertainty, such as agricultural innovation adoption. (Ragin, 2009; Woodside, 2013).

#### 5.2.1. Data Calibration

The fsQCA method was applied using the direct calibration approach in fs/QCA 3.0. Mean scores from 5-point Likert items were converted into fuzzy-set membership values with thresholds of 0.95 (full membership), 0.50 (crossover), and 0.05 (non-membership), following prior studies (Greckhamer et al., 2018; Pappas & Woodside, 2021a).[4]

#### 5.2.2. Configurations leading to high behavioral intention

Table 9 identifies three sufficient configurations (C1–C3) for high Behavioral Intention (BI), all with consistency above 0.80. Each pathway reflects how UTAUT-based factors jointly foster adoption.

- C1: Low perceived risk (PR) combined with strong social influence (SI) as a core condition, supported by effort (EE) and performance expectancy (PE), enhances BI—showing that minimized risk and trusted networks strengthen adoption.
- C2: Low PR with facilitating conditions (FC) and SI as core drivers leads to high BI, indicating that technical support and social endorsement reduce perceived barriers regardless of performance or effort perceptions.
- C3: Low PR with SI (core) and PE (peripheral) again promotes BI, suggesting that social validation and perceived usefulness jointly encourage adoption.

Collectively, these results confirm the central influence of social support and low perceived risk in shaping farmers' behavioral intention, aligning with prior studies (Pappas, 2021).

[4] . values ≥4.6 indicated full membership, around 3.0 indicated crossover, and ≤1.4 indicated full non-membership. Intermediate values (e.g., 3.8 or 2.2) were automatically interpolated by the software. This approach captures nuanced degrees of agreement, enhancing the configurational sensitivity of the analysis

**Table 9.** Configurations sufficient for high behavioral intention (BI) to adopt agrovoltaic systems.

| Configuration | Raw Coverage | Unique Coverage | Consistency | PR | FC | SI | EE | PE |
|---|---|---|---|---|---|---|---|---|
| C1 | 0.476 | 0.186 | 0.912 | ⊗♦ | | ●♦ | ●■ | ●■ |
| C2 | 0.392 | 0.164 | 0.898 | ⊗♦ | ●♦ | ●♦ | | |
| C3 | 0.398 | 0.124 | 0.889 | ⊗♦ | | ●♦ | | ●■ |

Note: ● indicates presence of a condition; ⊗ indicates absence; blank cells indicate a "don't care" condition, ♦ indicate core condition (present or absent), ■ indicate Peripheral condition (present or absent).

## 6. Discussion

The descriptive characteristics of the respondents provide an important contextual foundation for interpreting the findings of this study. The sampled farmers are, on average, middle-aged, highly experienced, and operate relatively large landholdings, indicating that they are key decision-makers capable of evaluating long-term investments such as agrovoltaic systems. At the same time, the predominance of low to medium education levels and the considerable share of farmers without prior experience in renewable energy or advanced agricultural technologies suggest a cautious and pragmatically oriented population. These characteristics help explain why economic and performance-related considerations play a central role in adoption decisions and why perceived risk emerges as a critical factor in this context.

The findings demonstrate that the UTAUT framework retains strong explanatory power in analyzing technology adoption behavior in the agricultural sector. The PLS-SEM results confirm that the core UTAUT constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—significantly shape farmers' behavioral intention to adopt agrovoltaic technologies. Among these, performance expectancy emerges as the strongest predictor, indicating that perceived productivity gains and economic returns remain the primary drivers of adoption decisions. This result is consistent with the broader technology adoption literature, which identifies performance expectancy as the most influential determinant of behavioral intention (Venkatesh et al., 2003a, 2012a). In agricultural contexts, prior studies likewise suggest that technologies closely linked to improved performance and cost efficiency are more likely to be adopted by (Aubert et al., 2012; Rezaei & Ghofranfarid, 2018). However, the present findings further indicate that in semi-arid and resource-constrained environments, the importance of performance expectancy is closely tied to livelihood security and economic risk considerations, underscoring the context-dependent applicability of UTAUT.

The moderating role of perceived risk adds an important theoretical dimension to these results. While performance expectancy exerts a direct positive effect on behavioral intention, this relationship weakens under conditions of high perceived uncertainty. This suggests that economic and technical benefits alone are insufficient to motivate adoption in risk-averse environments. Unlike much of the existing literature that conceptualizes perceived risk primarily as a direct barrier to adoption (Rezaei & Ghofranfarid, 2018), the findings of this study indicate that risk plays a contextual and interactive role by conditioning the extent to which enabling beliefs translate into behavioral intention. This interpretation aligns with more recent perspectives in the technology adoption literature that emphasize the dynamic and context-sensitive nature of risk perceptions (Pappas et al., 2016). The fsQCA results further complement this theoretical interpretation by revealing that high behavioral intention can emerge from multiple sufficient pathways. Across all successful configurations, low perceived risk and strong social influence consistently appear as core conditions, while the roles of performance expectancy, effort expectancy, and facilitating conditions vary depending on the specific combination of factors. This finding is consistent with complexity-oriented approaches to technology adoption, which argue that decision-making outcomes often result from alternative, context-dependent configurations rather than from single dominant predictors (Pappas & Woodside, 2021a). By integrating SEM and fsQCA, this study captures both linear relationships and configurational patterns, offering a more comprehensive understanding of farmers' adoption behavior.

From a theoretical perspective, this study contributes to the technology adoption literature by validating the applicability of the UTAUT framework in resource-constrained agricultural settings and by conceptualizing perceived risk as an interactive construct rather than merely a direct obstacle. The results suggest that analyzing adoption behavior in semi-arid agricultural systems requires approaches that explicitly acknowledge decision-maker heterogeneity, contextual dependency, and the presence of multiple pathways to adoption. Such an approach may also be valuable for future research examining technology adoption in other high-risk and resource-limited environments. Beyond the Iranian context, these findings contribute to the broader agrivoltaic and technology adoption literature by illustrating how UTAUT operates under resource constraints and how perceived risk shapes adoption not only as a barrier but also as a moderating condition. The integration of SEM and fsQCA highlights that adoption outcomes can arise from multiple configurational pathways, an insight that is relevant to semi-arid and resource-stressed agricultural systems more broadly.

## 7. Conclusions

This study examined Iranian farmers' behavioral intention to adopt agrovoltaic (AV) systems in a semi-arid, water-stressed agricultural context, with a particular emphasis on irrigation-related challenges. Using an integrated SEM–fsQCA approach grounded in the UTAUT framework, the findings indicate that farmers' adoption decisions are shaped primarily by expected improvements in irrigation-related performance and cost efficiency, as well as by perceived uncertainty surrounding system outcomes (Namdari, 2025) .

The SEM results demonstrate that performance expectancy is the strongest predictor of behavioral intention (Venkatesh et al., 2012b), highlighting the importance of farmers' expectations regarding productivity and irrigation-related benefits. At the same time, perceived risk exerts a significant negative effect and, importantly, moderates the relationship between performance expectancy and behavioral intention, particularly by weakening the influence of expected performance gains under conditions of high uncertainty. Complementary fsQCA findings further reveal that the absence of perceived risk and the presence of strong social influence consistently emerge as core conditions across all configurations leading to high adoption intention. Together, these results suggest that confidence in irrigation-related performance outcomes and trust-building mechanisms are more critical to AV adoption than technical considerations alone.

The main contribution of this study lies in empirically demonstrating that water-related performance expectations—rather than energy generation per se—constitute the dominant motivational pathway for agrovoltaic adoption in semi-arid Iran. Methodologically, the combined use of SEM and fsQCA advances technology adoption research by capturing both net effects and alternative causal configurations, thereby revealing the contextual and non-linear nature of farmer decision-making under water scarcity (Pappas et al., 2016; Pappas & Woodside, 2021b).

These findings have direct practical implications. For policymakers, the strong role of performance expectancy supports formally recognizing agrovoltaic systems as a dual-use water–energy innovation, with policy narratives explicitly anchored in irrigation performance and water-use reliability. For stakeholders and implementing agencies, the moderating effect of perceived risk underscores the need for context-specific de-risking instruments, such as pilot farms, performance guarantees, and risk-sharing mechanisms, to translate expected water-related benefits into credible adoption incentives. For local farming communities, the central role of social influence suggests that peer-based diffusion strategies, demonstration by early adopters, and trusted extension services are likely to be more effective than top-down promotion in encouraging adoption.

Finally, while this study is grounded in the Iranian context, its findings resonate with broader experiences in other water-stressed agricultural systems, indicating that water-oriented and risk-sensitive approaches to agrovoltaic deployment are likely to be relevant across semi-arid regions facing similar irrigation challenges. By situating agrovoltaic adoption within the wider challenge of sustainable agricultural water management, this study offers comparative insights for future research and policy design beyond Iran.

## Limitations and Future Research

This study provides new insights into farmers' behavioral intentions toward agrovoltaic (AV) adoption but has several limitations. First, the data originate from semi-arid regions of Iran, limiting generalizability; cross-country comparisons are needed to verify the identified configurations. Second, since AV systems are not yet widespread, findings rely on perceptions from hypothetical scenarios. Although useful for assessing earl behavioral intentions, longitudinal and pilot-based studies are required to validate results under real conditions. Finally, the analysis focused on individual-level factors within the UTAUT framework, excluding institutional dimensions such as cooperation and policy support. Future research should integrate these structural aspects to better capture context-specific adoption dynamics.

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# Appendix

**Appendix A.** Measurement Items for Latent Constructs and Their Sources.

| Construct (Code) | Item (English) |
|---|---|
| PE1 | Using agrovoltaic systems would enhance my farm productivity. |
| PE2 | Agrovoltaic systems can help reduce my irrigation costs. |
| PE3 | This technology would provide additional income (e.g., from electricity sales). |
| PE4 | Agrovoltaic systems are useful for climate-resilient farming. |
| EE1 | Learning to use agrovoltaic systems would be easy for me. |
| EE2 | I believe operating this technology is straightforward. |
| EE3 | Understanding how to use this system would be easy for me. |
| SI1 | People important to me think I should use agrovoltaic systems. |
| SI2 | Extension agents or cooperatives encourage me to use such technology. |
| SI3 | My peers support the adoption of agrovoltaic systems. |
| FC1 | I have the resources needed to implement agrovoltaic systems. |
| FC2 | There is adequate institutional support for this technology. |
| FC3 | I can get technical assistance if I want to adopt agrovoltaics. |
| PR1 | Adopting agrovoltaics is financially risky. |
| PR2 | I am concerned about the uncertainty of system performance. |
| PR3 | I think this technology may reduce my crop yields. |
| PR4 | Technical problems may arise during operation. |
| BI1 | I intend to adopt agrovoltaic systems in the near future. |
| BI2 | I am likely to use agrovoltaic systems if available. |
| BI3 | I plan to integrate agrovoltaics into my farm operations. |

**Appendix B –** Standardized Loadings for Measurement Items.

| Construct | Item | Loading |
|---|---|---|
| Performance Expectancy (PE) | PE1 | 0.79 |
| | PE2 | 0.81 |
| | PE3 | 0.76 |
| | PE4 | 0.62 |
| Effort Expectancy (EE) | EE1 | 0.82 |
| | EE2 | 0.79 |
| | EE3 | 0.77 |
| Social Influence (SI) | SI1 | 0.75 |
| | SI2 | 0.78 |
| | SI3 | 0.72 |
| Facilitating Conditions (FC) | FC1 | 0.76 |
| | FC2 | 0.74 |
| | FC3 | 0.71 |
| Perceived Risk (PR) | PR1 | 0.81 |
| | PR2 | 0.79 |
| | PR3 | 0.76 |
| | PR4 | 0.74 |
| Behavioral Intention (BI) | BI1 | 0.83 |
| | BI2 | 0.80 |
| | BI3 | 0.78 |

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# نیت رفتاری کشاورزان برای پذیرش سامانه‌های اگروولتائیک در مناطق نیمه‌خشک ایران: یافته‌هایی از مدل‌سازی معادلات ساختاری و تحلیل کیفی تطبیقی مبتنی بر مجموعه‌های فازی

**شیرین ظریف مرادیان، و محمود دانشور کاخکی**

**چکیده**

کمبود آب و ناامنی انرژی، کشاورزی پایدار را در مناطق نیمه‌خشک مانند ایران با تهدید مواجه کرده و بر ضرورت نوآوری‌هایی همچون سامانه‌های اگروولتائیک (AV) تأکید می‌کند. این مطالعه در شهرستان فریمان، به‌عنوان یک منطقه کشاورزی دچار تنش آبی در شمال‌شرق ایران، انجام شده و عوامل تعیین‌کننده نیت رفتاری کشاورزان ایرانی برای پذیرش فناوری اگروولتائیک را بر اساس داده‌های پیمایشی گردآوری‌شده از ۲۱۵ کشاورز آبیاری‌شونده مقیاس بزرگ و از طریق پرسشنامه حضوری بررسی می‌کند. این پژوهش از یک رویکرد ترکیبی بهره می‌گیرد که مدل‌سازی معادلات ساختاری (SEM)و تحلیل کیفی تطبیقی مبتنی بر مجموعه‌های فازی (fsQCA) را تلفیق می‌کند. این مطالعه با تکیه بر نظریه یکپارچه پذیرش و استفاده از فناوری (UTAUT)، عوامل رفتاری و زمینه‌ای کلیدی مؤثر بر نیت رفتاری کشاورزان برای پذیرش سامانه‌های اگرووولتائیک را بررسی می‌کند. نتایج SEM نشان می‌دهد که منافع ادراک‌شده، ملاحظات سهولت استفاده و تأثیرات اجتماعی به‌طور معناداری نیت رفتاری را شکل می‌دهند و بخش قابل‌توجهی از واریانس نیت رفتاری را تبیین می‌کنند ($R^2 = 0.58$) در حالی که ادراک ریسک اثر منافع ادراک‌شده را تضعیف می‌کند. نتایج fsQCA سه مسیر جایگزین منتهی به نیت رفتاری بالا را شناسایی می‌کند که همگی با ریسک ادراک‌شده پایین و تأثیر اجتماعی قوی مشخص می‌شوند. یافته‌ها نشان می‌دهد که عوامل روان‌شناختی و اجتماعی به اندازه عوامل فنی و اقتصادی اهمیت دارند. بنابراین، سیاست‌گذاری‌ها باید بر کاهش ریسک‌های ادراک‌شده و بهره‌گیری از شبکه‌های اجتماعی به‌منظور تسریع پذیرش سامانه‌های اگروولتائیک در کشاورزی دچار تنش آبی تمرکز کنند.