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Applying social cognitive theory to examine farmer migration in response to groundwater salinity: The case of Qaenat, Iran

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ABSTRACT

Adverse climatic conditions and excessive groundwater extraction have jeopardized agriculture and water resources, caused the salinization of agricultural wells and prompted widespread rural-to-urban migration. To develop effective decentralization policies, it is crucial to analyze farmers' migration behavior in response to increasing water salinity. This study applies the Extended Social Cognitive Theory (ESCT) to explore these dynamics. This study employs a descriptive-survey research method, with the statistical population comprising farmers in Qaenat County, South Khorasan Province. A proportional random sample of 300 farmers was selected and surveyed using a researcher-developed questionnaire. The validity of the questionnaire was confirmed through expert opinions, while its reliability was assessed using Cronbach's alpha coefficient, ranging from 0.6 to 0.95. The Structural Equation Modeling (SEM) analysis revealed that the perception of others' behavior (POB), attitudes, and perceived barriers significantly predict the willingness to adapt to water salinity through both technical and non-technical methods. Furthermore, the findings revealed that the ESCT accounted for 48.4 % of the variance in farmers' migration intentions and 29.5 % of the variance in their actual migration behavior. Among the examined factors, perceived behavior of others, attitudes, and social capital emerged as key determinants of migration behavior, while moral norms exerted the strongest influence on migration intentions. These results underscore the critical role of socio-cognitive variables in shaping adaptive responses to the challenges posed by water salinity. Future research could apply various behavioral models to investigate both technical and non-technical adaptation strategies, offering a more comprehensive understanding of how individuals respond to environmental challenges across different contexts.

1. Introduction

Climate change and water scarcity are critical challenges that directly affect water security (Pakmehr et al., 2020; Mehrazar et al., 2020; Paudel et al., 2020) and agricultural production (Mehrazar et al., 2020; Savari et al., 2022). These impacts are becoming increasingly evident, particularly in arid and semi-arid regions across the globe (DeNicola et al., 2015), including Iran (Yazdanpanah et al., 2024; Daneshvar et al., 2019; Rouzaneh et al., 2021). People's responses to climate uncertainty and the complexity of socio-ecological systems depend largely on their capacity to learn about environmental resources and crises, and adapt accordingly (Galaz, 2005). This is especially critical in agriculture, where farmers' adaptive strategies play a vital role in reducing vulnerability and mitigating the adverse effects of climate change (Yazdanpanah et al., 2023; Bandyopadhyay et al., 2011; Savari and Amghani, 2022).

One of the most significant consequences of these environmental changes is the degradation of water quality, particularly the rise in water salinity (Cominelli and Tonelli, 2010; Rahimi-Feyzabad et al., 2022a,b; DeNicola et al., 2015; Shadkam et al., 2016). Water salinity represents a major constraint on agricultural production as it leads to soil infertility and reduced crop yields, which ultimately forces farmers to abandon their lands and migrate to urban areas (Singh, 2015). Rising groundwater salinity, exacerbated by over-extraction and climate change, poses a significant threat to global food security (Mitra et al., 2021). Groundwater depletion and increased salinity are among the primary threats to the sustainability of agriculture (Pulido-Bosch et al., 2018). Approximately 70 % of global groundwater extraction is used for

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irrigation (Birkenholtz, 2017), and climate change is a key driver of increased salinity (Akbari et al., 2020). These challenges may become critical issues for global food security, particularly in Asia (IPCC, 2014).

In Iran, over one-third of irrigated lands are affected by salinity issues (Cano and Campos, 2024; Cheraghi, 2004), which pose serious threats to food security, environmental stability, and sustainable development (Bandyopadhyay et al., 2011; Savari and Amghani, 2022). The use of saline groundwater for irrigation has emerged as a significant constraint to agriculture, resulting in economic losses for farmers, particularly for smallholder farmers who are more vulnerable to these changing conditions (Mandal et al., 2016). Understanding farmers' perceptions of these changes is critical for developing policies that support effective adaptation strategies.

Rising groundwater salinity is a substantial threat to both the well-being of individuals and their livelihoods. Increased salinity not only reduces crop yields but also diminishes the nutritional and economic value of the produce, leading to a decline in farmers' revenue (El-Fadel et al., 2018). The adaptation of farmers to these challenges is heavily influenced by their perceptions of the issue (Deressa et al., 2011; Feola et al., 2015). Effective adaptation involves two key steps: recognizing climate change and its associated risks, and responding to these changes to mitigate their negative impacts (Tripathi and Mishra, 2017). Given the economic vulnerability of smallholder farmers, migration has become a significant adaptive strategy in regions experiencing salinity challenges.

Despite its importance, relatively few studies have examined the socio-economic impacts of agricultural water salinity. For instance, Hassani et al. (2020) estimated that approximately 85,350 ha of agricultural land in Mozambique are affected by salinity. At a broader scale, studies have investigated the effects of increasing salinity levels on crop yields, with remote sensing-based estimates showing that salt stress limits the ability of plants to absorb water (Ivushkin et al., 2019; Madrigal et al., 2003). In saline soils, crop yields can decrease by over 50 % due to reduced fertility (Anami et al., 2020; Ivushkin et al., 2019). Furthermore, spatial distribution maps of saline areas (FAO, 2021) and global datasets (Hasegawa et al., 2022) have been used to assess the impact of climate change on crop yields, while studies have also explored the role of salt-tolerant varieties in improving crop performance (Challinor et al., 2014).

Most existing migration studies have focused on sea-level rise (SLR) migration in coastal areas due to flooding risks (Reimann et al., 2023; Hauer et al., 2020). However, fewer studies have examined the effects of salinity and SLR on migration. For example, Chen and Mueller (2018) investigated migration patterns in coastal Bangladesh, and Duc Tran et al. (2023) assessed rural out-migration in Vietnam's Mekong Delta, noting the relationship between household vulnerability to salinity intrusion and migration. Additionally, models like the Dynamic Interactive Vulnerability Assessment (DIVA) have been used to simulate the impact of salinity on migration (Vafeidis et al., 2004; Hinkel and Klein, 2009), though such models often fail to account for salinity intrusion into coastal aquifers. Decision-making models regarding adaptation and migration under various salinity scenarios have also been explored but typically require large datasets for meaningful analysis (Chen and Mueller, 2018).

In South Khorasan Province, drought-induced groundwater depletion has resulted in increased salinity in agricultural wells (Foster et al., 2018; Scanlon et al., 2007). This salinity reduces water quality and negatively affects agriculture, leading to lower crop yields and substantial income declines for farmers (Mazumder et al., 2022; Sharma and Minhas, 2005; Akbari et al., 2020). As a result, rural migration has become an important adaptive strategy, particularly for small-scale and landless farmers who lack adequate drought mitigation measures. However, migration often results in socio-economic conflicts, especially as farmers seek employment in urban areas (Sultana Jahura and Mostafa, 2024).

Given that farmers are key stakeholders in the implementation of adaptive policies and programs, understanding their behavior and the factors influencing their adaptive capacity is essential for enhancing agricultural stability and promoting food security (Hume, 2020; Viola et al., 2016; Fadina and Barjolle, 2018). Migration, as an adaptive response, requires particular attention due to its potential to increase farmers' vulnerability. Therefore, it is crucial to understand how psychological factors influence farmers' decision-making processes in the face of climate-induced challenges.

Contemporary socio-psychological frameworks, such as the Theory of Planned Behavior (TPB) (Ajzen, 1985), the Value-Belief-Norm Theory (Schwartz, 1977), and the Protection Motivation Theory (PMT) (Rogers, 1975; Bijani et al., 2022), offer valuable insights into individuals' adaptation to climate change. Moreover, models like the Private Proactive Adaptation Model to Climate Change (Grothmann and Patt, 2005), the Mitter Model (Mitter et al., 2019), and the Social Cognitive Readiness Model (SCRM) (Paton, 2003) have contributed to understanding adaptive behaviors. Social Cognitive Theory (SCT), particularly, has been applied to assess water conservation behaviors among farmers (Yazdanpanah et al., 2014), focusing on factors like self-efficacy, outcome expectations, and the role of social learning in shaping adaptive behaviors (Bandura, 1997; Phipps et al., 2013; Yazdanpanah et al., 2015).

Given the challenges presented by climate change in South Khorasan Province (East of Iran), particularly groundwater salinization, this study seeks to explore the adaptive strategies employed by farmers in response to these pressures. By focusing on farmers' perceptions and behavioral responses, the research aims to provide insights into the factors influencing their adaptation decisions and the role of migration in these strategies.

2. Theoretical framework

The **Social Cognitive Theory (SCT)**, developed by Bandura (1986), offers a robust framework for understanding the interplay between personal, environmental, and behavioral factors in shaping human actions (Wu et al., 2022; Young et al., 2005). It has been widely applied to health behaviors (Bandura, 2004) and environmental challenges, exploring how thoughts, emotions, and actions are influenced by perceived capabilities and social context (Li et al., 2024).

At its core, SCT emphasizes reciprocal determinism, where behavior is both influenced by and an influencer of personal and environmental factors. Central to this theory is self-efficacy—an individual's belief in their ability to successfully perform behaviors—along with outcome expectations, or the anticipated consequences of those behaviors, both of which significantly shape behavioral intentions (Bandura, 1977, 2001; Ganesh and Chatterjee, 2021). Additionally, SCT highlights the role of observational learning, where individuals model behaviors observed in others, which can reinforce or modify their actions.

In examining non-technical migration behaviors among farmers in South Khorasan, facing salinity in agricultural wells, SCT provides valuable insights. The theory's dynamic approach—focusing on the interaction between personal agency and environmental factors—is effective for analyzing how farmers adapt to environmental stressors like water salinity (Yazdanpanah et al., 2015). This framework not only aids in understanding migration determinants but also forms the basis for designing interventions to promote sustainable adaptation strategies.

To fully understand farmers' responses to agricultural water salinity and migration decisions, additional variables can be integrated within the SCT framework as ESCT. These include attitudes, subjective norms, moral norms, perceived sensitivity, perceived severity, perceived barriers, perceived benefits, social capital, and social discourse. These factors collectively influence farmers' decisions to stay or migrate. For example, self-efficacy affects migration intentions and behaviors, while social capital—comprising networks, trust, and community support—can either facilitate or hinder migration by providing essential resources. Incorporating these variables into SCT (ESCT) enhances our ability to analyze farmers' behaviors and design targeted policies to address non-technical migration.

Based on the literature, the following hypotheses are proposed:

1. Self-efficacy, attitudes, perceived sensitivity, perceived severity, and social capital significantly influence migration intentions.
2. Perceived barriers, perceived benefits, and social discourse impact migration intentions.
3. Migration behaviors are directly influenced by migration intentions, self-efficacy, and social capital.
4. Perceived sensitivity, perceived severity, perceived barriers, and perceived benefits significantly affect migration behaviors.
5. Social norms and social discourse indirectly influence migration behaviors through their impact on migration intentions.

3. Materials and methods

3.1. Justification for PLS-SEM and social cognitive theory (SCT) selection

The Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was selected for this study due to its capacity to handle complex theoretical frameworks and estimate intricate relationships among multiple independent and dependent variables. Given the predictive nature of this research, which aims to examine farmers' non-technical migration behaviors, PLS-SEM's emphasis on maximizing explained variance (R^2) aligns well with the study's objectives. Moreover, its suitability for small to medium sample sizes ensures the reliability of results despite the limited accessibility to large datasets (Akter et al., 2017). Additionally, PLS-SEM effectively accommodates both reflective (e.g., perceived severity and self-efficacy) and formative constructions (e.g., perceived barriers), strengthening the robustness of the measurement and structural models (Machfudiyanto et al., 2023). To explore farmers' adaptive responses to groundwater salinity, the Social Cognitive Theory (SCT) was adopted as the behavioral framework due to its comprehensive and flexible nature. SCT offers a multidimensional approach by integrating cognitive, social, and environmental factors that influence behavioral adaptation, emphasizing human agency and observational learning. Its empirical success in agricultural and environmental studies, particularly in analyzing pro-environmental and adaptation behaviors, further justifies its selection (Saad, 2024). The theory's ability to incorporate additional variables such as perceived sensitivity, perceived severity, and social capital allows for a more nuanced examination of farmers' migration decisions. By leveraging SCT within the PLS-SEM framework, this study provides a robust analytical approach to understanding adaptive behaviors, generating valuable insights for policymaking and sustainable agricultural strategies in salinity-affected regions (Ayanwale et al., 2023).

3.2. Case study: qaenat county, south khorasan province

A cross-sectional, non-experimental survey was conducted to test the research hypotheses. The respondents were farmers from Qaenat County, located in South Khorasan Province, Iran. Qaenat County, situated in eastern Iran, spans an area of 7502 square kilometers. According to the Statistical Center of Iran (2017), the population of Qaenat County was 114,729, with 44,043 individuals living in rural areas. South Khorasan is characterized by a harsh desert climate, receiving an average annual precipitation of less than 180 mm (Modiri et al., 2016). The region is subject to significant temperature fluctuations, with winter lows averaging -3 °C and summer highs exceeding 40 °C (Amirabadizadeh, 2019). Despite these challenging climatic conditions, Qaenat is recognized as a key agricultural area within the province. The county is divided into several districts, each comprising multiple villages that were included in the study.

3.3. Sampling and questionnaire design

The target population of this study included the farmers in the county (N = 250) (Jihad-e-Agriculture Organization of Qaen County, 2024). Qaen County is situated in South Khorasan Province and it consists of three districts: Central, Sedeh, and Nimbeluk, with the Central and Nimbeluk districts being the focus of this research. A stratified multistage sampling method selected a representative sample, resulting in 300 respondents from 15 villages. The sample size was initially calculated to be 209 using Cochran's formula (Kotrlik and Higgins, 2001); however, it was increased to 300 to ensure adequacy. This descriptive, causal, and correlational study was conducted through a survey.

The instrument utilized in this study was a questionnaire designed with closed-ended questions, whose validity was assessed and confirmed by experts and faculty members in agricultural extension and education. The reliability of the questionnaire was determined using Cronbach's alpha test among 30 farmers in the county for the variables evaluated on a Likert scale. The calculations indicated that the questionnaire's reliability was acceptable (Table 1). The necessary data were collected through face-to-face surveys. It is noteworthy that respondents were not allowed to participate in the survey or answer questions during the data collection process. After the field study, 320 questionnaires were completed. Ultimately, 300 questionnaires were analyzed. The software used for data analysis was SPSS24. A 5-point Likert scale (0: very low, 1: low, 2: medium, 3: high, and 4: very high) was employed to measure the variables of NTBM, IM, POB, and OE. Additionally, the variables of perceived susceptibility, perceived severity, perceived benefits, perceived barriers, attitude and social discourse were used as auxiliary variables for development. Table 1 lists the items used to measure each variable. Furthermore, the items used to assess each variable in this study were extracted from previous studies. Without suitable items for variable measurement, researcher-developed items, validated by experts, were incorporated.

3.4. Data analysis

The data were analyzed using SPSS and SmartPLS4.1.0.2 software. SPSS was employed for descriptive statistics, a crucial initial step in data preprocessing and screening, particularly in quantitative studies. SmartPLS 4.1.0.2, the primary software for PLS-SEM (Partial Least Squares Structural Equation Modeling), is frequently utilized for designing new study models. This study opted for PLS-SEM over covariance-based structural equation (CB-SEM) due to its practicality and the fact that it does not require data normality. Additionally, PLS-SEM can analyze study models with relatively small sample sizes that include numerous indicators and paths. Furthermore, PLS-SEM is a non-parametric algorithm used to determine the value of each latent variable. The analysis stages include data entry, structure measurement, discriminant validity analysis, and determining the relationships between structural variables. In studies employing the PLS-SEM approach, attention to several recommended indices is crucial.

The significance level must be below 0.05 for the relationships between variables to be declared significant. The model must have sufficient explanatory power, with R^2 values not falling below 0.25. In PLS-SEM, for evaluating measurement and structural models, The Root Mean Square Error of Approximation (RMSEA) was reported with a value less than 0.08 indicating a better fit (Hair et al., 2017; Kline, 2012). Convergent validity was assessed based on three criteria: (1) factor loadings greater than 0.5, (2) Average Variance Extracted (AVE) greater than 0.50, and (3) Composite Reliability (CR) greater than 0.70 for the measurement variables. To evaluate structural models, path coefficients indicating the strength and direction of relationships between latent constructs are reviewed. Bootstrap techniques are employed to estimate the significance of these coefficients. Assessing effect sizes, such as R^2 values, provides further clarity on the proportion of variance in

Table 1
Cronbach's alpha coefficients and items of the research variables.

Variables	Items	Source
Attitude	For me, adopting technical methods to prevent the salinization of water is pleasant. For me, adopting technical methods to prevent the salinization of water is appealing. For me, adopting technical methods to prevent the salinization of water is reasonable. For me, adopting technical methods to prevent the salinization of water is a good practice. In my opinion, using technical methods in agriculture to prevent the salinization of water is a commendable practice. In my opinion, using technical methods during farming to prevent the salinization of water is beneficial. In my opinion, using technical methods during irrigation to prevent the salinization of water is necessary.	Ajzen, (2002); Faisal et al. (2020)
Moral Norm	I feel a sense of responsibility to effectively combat water salinity by implementing technical methods. I believe that, regardless of what other farmers do, I should effectively prevent water salinity through technical methods based on my own values. I feel that by effectively preventing water salinity through technical methods, I am personally contributing to a greater good. I believe that adopting technical methods makes me a better farmer in mitigating the process of water salinization. I feel a greater sense of well-being when I engage in behaviors that combat water salinity.	
Subjective Norm	Most of the people who are important to me believe that I should combat water salinity by adopting technical methods. Most of the people who are important to me expect me to combat water salinity by adopting technical methods. The individuals whose opinions I value prefer that I combat water salinity by adopting technical methods. I should implement adaptive measures (technical methods) against increasing water salinity because my friends and neighbors expect me to do so. Other farmers believe that I should adopt adaptive measures (technical methods) to counteract increasing water salinity. Society expects me, as a farmer and a primary water consumer, to use less water to help mitigate the progression of water salinity. Most of the people who are important to me encourage me to adopt technical methods to combat increasing water salinity. Most of the people who know me support my adoption of technical methods to combat increasing water salinity. Many people assist me when water salinity poses a serious threat.	Shahangian et al. (2021a), (2021b); Zobeidi et al. (2022)
Perception of Others' Behavior	My family always pays attention to water salinization and ways to combat it. My friends and acquaintances do whatever they can to reduce water salinization and apply technical methods to combat it. Engaging in behaviors to combat water salinization is viewed as highly important and necessary by significant people in my life, such as family, friends, and acquaintances. How much do you think individuals with your social standing (e.g., education and income) participate in behaviors to combat water salinization?	Thøgersen and Grønhøj (2010); Yazdanpanah et al. (2015); Valizadeh et al. (2020)
Perceived Sensitivity	I believe that excessive extraction of healthy water leads to water salinization. I think that social vitality among farmers will decrease due to increasing water salinization. I believe that the rising trend of water salinization will likely damage the quality of agricultural products. I think failing to implement technical methods will likely result in water salinization. I believe that increasing water salinization will cause conflicts among farmers.	Hoan et al. (2019); Zobeidi et al. (2021)
Perceived Severity	In my opinion, water salinization has damaged crops. I believe that water salinization leads to migration to cities and the depopulation of villages. I think that if the current trend of water salinization continues, we will soon experience despair, depression, and anxiety. In my opinion, agricultural water salinization is a severe threat to the income and livelihood of farmers. I believe that soil fertility reduction due to increasing water salinization will significantly harm my agricultural production and income.	Feng et al. (2017); Zobeidi et al. (2021)
Social Discourse	My family members or friends talk to me about the risk of increasing water salinity. My neighbors talk to me about the risk of increasing water salinity. I receive information about the risk of increasing water salinity	

(*continued on next page*)

Table 1 (*continued*)

Variables	Items	Source
	and the implementation of technical methods from local television and radio.	
Perceived Barriers	Farmers do not believe in using technical methods (…) to combat the increasing trend of water salinity.	
	Instead of adopting policies to prevent the increasing trend of water salinity by encouraging the use of technical methods (…), government organizations place more emphasis on water quantity and accessibility.	
	Financial constraints and lack of capital significantly hinder the implementation of measures to combat water salinity.	
	Using technical methods (…) to combat water salinity requires adopting new habits, which is difficult.	
	Using technical methods (…) to combat water salinity makes agricultural activities and crop production more challenging.	
	Given my work commitments, combating water salinity through the implementation of technical methods is exhausting for me.	
Social Capital	My community is highly united in combating the increasing trend of water salinity.	
	A member of my community would certainly help me when needed to combat water salinity.	
	If others also participate, I am more likely to take part in community projects aimed at combating water salinity.	
	If I learned new information on how to better prepare for combating water salinity, I would share it with my community.	
	The community is experiencing conflicts due to water salinity.	
Perceived Benefits	Implementing technical methods (such as water conservation, crop pattern changes, water treatment, and the use of greywater) to protect water resources from salinity contributes to strengthening the regional and national economy.	
	Implementing technical methods (such as water conservation, crop pattern changes, water treatment, and the use of greywater) to protect water resources from salinity supports rural development.	
	By adopting technical (…) and non-technical methods (such as land-use change, job transition, and migration) to protect water resources from salinity, we can preserve water for future generations.	
	Using technical methods (…) not only protects water resources from salinity but also preserves agricultural crops.	
	Using technical methods (…) to protect water resources from salinity helps strengthen the economy of my region and country.	
	Preventing the increase in water salinity also preserves other resources, such as soil and biodiversity.	
Self-Efficacy	I can easily change my agricultural and irrigation practices to combat water salinity.	
	I am capable of adapting to the risks and impacts of increasing water salinity.	
	I know how to take precautionary measures in agriculture regarding increasing water salinity.	
	I can modify my current agricultural practices to prevent water salinity.	
	I can actively participate in combating water salinity through technical methods; it is entirely feasible for me.	
	I know that participating in combating water salinity by implementing technical methods is very easy.	
Intention to Migrate	I intend to persuade others to adopt technical methods to combat the trend of water salinization.	Zobeidi et al. (2021); Azadi et al. (2019)
	I plan to adopt technical methods to combat the trend of water salinization.	
	To what extent might you use technical methods to combat water salinization? (High, Medium, Low)	
Migration Behavior	With excessive water salinization, I am forced to abandon my land in the village.	Zobeidi et al. (2021); Azadi et al. (2019)
	With excessive water salinization, I am forced to relocate my residence.	

endogenous constructs explained by their exogenous counterparts.

4. Results

To evaluate the measurement model in the PLS-SEM method, the validity and reliability of each construct are assessed using the CFA technique. As observed in Table 2, all item loadings exceed the minimum threshold of 0.7, indicating a satisfactory level of agreement for the construct. The CR value must be above 0.7 as each construct demonstrates good internal consistency. In this study, the CR values range from 0.7 to 0.9, indicating no issues with internal consistency. Furthermore, the AVE value should be above the 0.5 threshold to ensure good convergent validity of the construct. The lowest AVE value is 0.5, which meets the minimum criterion. Finally, Cronbach's alpha values range from 0.7 to 0.896, exceeding the 0.6 threshold recommended by Hair.

According to Kock's recommendation, the PLS-SEM method requires a collinearity test to determine if the collected data have multi-collinearity issues. The multi-collinearity test was conducted by analyzing the Variance Inflation Factor (VIF) values. This study found that the VIF values do not exceed 3.3, as shown in Table 3, indicating no issues with multi-collinearity. Discriminant validity was analyzed using the Fornell-Larcker test. Table 4 demonstrated that the study possesses good discriminant validity, where the AVE values of each construct are higher than those of others. Fig. 1 illustrates the behavioral model based

Table 2
Results for reliability and convergent validity test.

Behavioral Variables	Cronbach's alpha	Composite Reliability rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
Perceived Sensitivity	0.782	0.796	0.837	0.501
Self-Efficacy	0.808	0.875	0.842	0.574
Perception of Others' Behavior	0.714	0.714	0.814	0.503
Social Capital	0.701	0.751	0.805	0.501
Perceived Severity	0.802	0.808	0.862	0.556
Perceived Benefits	0.742	0.752	0.818	0.503
Migration	0.845	0.845	0.928	0.865
Perceived Barriers	0.786	0.783	0.813	0.51
Attitude	0.863	0.912	0.89	0.52
Intention	0.828	0.868	0.872	0.536
Moral Norm	0.828	0.852	0.876	0.545
Subjective Norm	0.897	0.907	0.916	0.552
Social Discourse	0.752	0.759	0.856	0.666

on Social Cognitive Theory, demonstrating the explanatory variance of farmers' non-technical intentions and behaviors in response to the salinity of agricultural well water, as compared to Fig. 2, which represents the extended version of the Social Cognitive Theory.

Model fit in Smart PLS can be observed from the SRMR, d-ULS, and d_G values. The discrepancy between the observed correlation and the model matrix is evident in the SRMR value. A good SRMR value is less than 0.08, and this study has an SRMR value of 0.078 (Table 5). Additionally, the differences between the covariance matrix and the empirical covariance matrix in d-ULS and d_G are listed using the composite factor model. It is concluded that this study meets the requirements of a well-fitted model.

Table 6, presents the standardized total effects, direct effects, and indirect effects of variables in the extended social cognitive model, aimed at examining factors influencing the non-technical behavior of farmers. As shown in Table 7 and Fig. 2, variables such as moral norms (Beta=0.364, $P < 0.001$), perceived sensitivity (Beta=0.104, $P < 0.05$), and social capital (Beta=0.356, $P < 0.001$) have a positive, direct, and significant impact on the intention variable, with moral norms exerting the most decisive influence among these factors. Collectively, these variables can predict 48.4 % of the variations in intention. Additionally, the intention variable (Beta= −0.195, $P < 0.01$) has a direct, negative, and significant impact on non-technical behavior (migration).

Variables like the perception of others' behavior (Beta=0.358, $P < 0.001$), attitude (Beta=0.199, $P < 0.001$), social capital (Beta=0.223, $P < 0.005$), perceived sensitivity (Beta= −0.138, $P < 0.05$), perceived severity (Beta=0.130, $P < 0.03$), and perceived barriers (Beta=0.229, $P < 0.0001$) have a positive/negative, direct, and significant effect on the behavior variable, with attitude showing the most decisive influence among these factors. Collectively, these variables can predict 29.5 % of the variations in behavior.

In conclusion, the extended social cognitive model for examining factors influencing the non-technical behavior (migration) of farmers can predict 48.4 % and 29.5 % of the variations in the intention and behavior variables, respectively. Other relationships in the proposed model were not significant.

5. Discussion

As highlighted in the results section, the main hypotheses regarding farmers' migration behavior in response to agricultural well water

Table 3
Results for multi-collinearity test.

Variable	VIF
Sensitivity− > Migration	2.249
Sensitivity− > Intention	2.218
Self − efficacy− > Migration	1.437
Self − efficacy− > Intention	1.429
Perceptionofothers'behaviors− > Migration	2.08
Perceptionofothers'behaviors− > Intention	2.054
Socialcapital− > Migration	1.791
Socialcapital− > Intention	1.558
Severity− > Migration	2.078
Severity− > Intention	2.06
Benefits− > Migration	1.99
Benefits− > Intention	1.966
Barriers− > Migration	1.251
Barriers− > Intention	1.25
Attitude− > Migration	2.131
Attitude− > Intention	2.129
Intention− > Migration	1.851
Moralnorms− > Migration	2.449
Moralnorms− > Intention	2.198
Subjectivenorms− > Migration	2.479
Subjectivenorms− > Intention	2.436
Socialdiscourse− > Migration	1.32
Socialdiscourse− > Intention	1.32
Sensitivity− > Migration	2.249
Sensitivity− > Intention	2.218
Self − efficacy− > Migration	1.437

Table 4
Results of the Fornell-Larcker test for assessing discriminant validity. All bolded loadings in the diagonal dimensions are the square root values of AVE.

	Perceived Sensitivity	Self-Efficacy	Perception of Others' Behavior	Social Capital	Perceived Severity	Perceived Benefits	Migration	Perceived Barriers	Attitude	Intention	Moral Norm	Subjective Norm	Social Discourse
Perceived Sensitivity	**0.629**												
Self-Efficacy	0.197	**0.688**											
Perception of Others' Behavior	0.298	0.326	**0.684**										
Social Capital	0.243	0.388	0.511	**0.679**									
Perceived Severity	0.693	0.17	0.306	0.198	**0.746**								
Perceived Benefits	0.475	0.311	0.447	0.361	0.451	**0.629**							
Migration	0.14	0.141	0.35	0.296	0.22	0.181	**0.93**						
Perceived Barriers	0.373	0.132	0.24	0.196	0.283	0.344	0.304	**0.578**					
Attitude	0.447	0.282	0.458	0.395	0.417	0.561	0.35	0.332	**0.693**				
Intention	0.331	0.238	0.41	0.544	0.25	0.444	0.115	0.187	0.431	**0.732**			
Moral Norm	0.432	0.395	0.429	0.414	0.438	0.597	0.233	0.219	0.627	0.553	**0.738**		
Subjective Norm	0.398	0.469	0.637	0.401	0.379	0.533	0.262	0.273	0.56	0.33	0.558	**0.743**	
Social Discourse	0.241	0.3	0.399	0.295	0.192	0.26	0.054	0.115	0.142	0.201	0.226	0.382	**0.816**

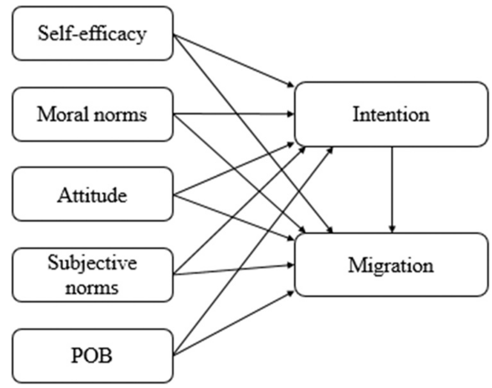

Fig. 1. The primary model.

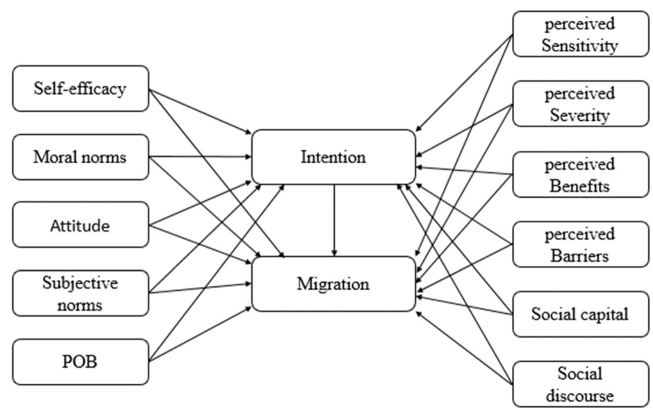

Fig. 2. The final model.

Table 5
Results of model fit.

	Saturated Model	Estimated Model
SRMR	0.072	0.079
d_ULS	26.031	26.031
d_G	7.795	7.795
Chi-square	10224.8	10224.8
NFI	0.433	0.433

salinity were tested, and some were confirmed. Accordingly, the component of the perception of others' behavior within the framework of social cognitive theory (SCT) had a positive and significant effect on non-technical migration behavior.

Attitude, as a cognitive variable, is significantly associated with behaviors triggered by environmental stressors such as water salinity. The structural model results in this study reveal that attitude has a direct and positive impact on behavior (Beta=0.199, $P < 0.05$). Research indicates that a positive attitude toward adaptive behaviors can lead to more proactive responses to environmental challenges. For instance, studies demonstrate that farmers with a positive outlook on sustainable water management practices are less likely to migrate and are more inclined to adopt innovative solutions to mitigate the effects of salinity (Bandura, 1986; Rana and Dwivedi, 2015).

Moreover, the integration of attitude within SCT posits that farmers' perceptions and evaluations of water salinity issues directly influence their decision-making processes. A positive attitude towards adaptive measures enhances self-efficacy and outcome expectations, thereby reducing the likelihood of migration (Phipps et al., 2013).

Empirical studies emphasize the mediating role of attitude in the relationship between perceived environmental stress and migration

Table 6
Results of the initial hypothesis test.

Direct Effect	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Sensitivity -> Migration	−0.17	−0.166	0.083	2.048	0.041
Sensitivity -> Intention	0.13	0.136	0.064	2.032	0.042
Self-efficacy -> Migration	0.002	0.006	0.073	0.029	0.977
Self-efficacy -> Intention	−0.064	−0.049	0.051	1.256	0.21
Perception of others' behaviors -> Migration	0.229	0.225	0.074	3.105	0.002
Perception of others' behaviors -> Intention	0.118	0.118	0.071	1.656	0.098
Social capital -> Migration	0.136	0.142	0.062	2.202	0.028
Social capital -> Intention	0.355	0.355	0.055	6.459	0.000
Severity -> Migration	0.17	0.168	0.067	2.55	0.011
Severity -> Intention	−0.1	−0.098	0.062	1.617	0.106
Benefits -> Migration	−0.136	−0.131	0.069	1.981	0.048
Benefits -> Intention	0.114	0.107	0.052	2.172	0.03
Barriers -> Migration	0.227	0.237	0.055	4.095	0.000
Barriers -> Intention	−0.012	−0.01	0.047	0.256	0.798
Attitude -> Migration	0.217	0.206	0.084	2.582	0.01
Attitude -> Intention	0.033	0.031	0.064	0.506	0.613
Intention -> Migration	−0.171	−0.17	0.072	2.379	0.018
Moral norms -> Migration	−0.001	0.001	0.077	0.012	0.99
Moral norms -> Intention	0.368	0.361	0.067	5.527	0.000
Subjective norms -> Migration	−0.014	−0.016	0.088	0.154	0.878
Subjective norms -> Intention	−0.151	−0.15	0.075	2.009	0.045
Social discourse -> Migration	−0.086	−0.088	0.066	1.309	0.191
Social discourse -> Intention	−0.002	0.002	0.049	0.031	0.975

behavior. For example, Yazdanpanah et al. (2015) found that farmers with favorable attitudes towards environmental sustainability exhibited lower migration tendencies, underscoring the importance of cognitive variables in SCT (Yazdanpanah et al., 2015). Furthermore, structural equation modeling conducted by Rana and Dwivedi (2015) revealed that attitude significantly predicts farmers' behavioral intentions regarding migration, confirming its crucial role within the SCT framework (Rana and Dwivedi, 2015).

Overall, incorporating attitude into SCT provides a comprehensive understanding of the factors driving migration behavior among farmers facing water salinity issues. This expanded framework highlights the importance of cognitive evaluations and their implications for adaptive behaviors and migration decisions (Bandura, 1986; Thøgersen and Grønhøj, 2010).

Incorporating perceived barriers as an additional variable in the SCT is crucial for understanding the migration behavior of farmers facing well water salinity. Perceived barriers refer to an individual's assessment of obstacles that hinder the execution of a particular behavior (Bandura, 1986; Schwarzer, 2008). These barriers can significantly influence decision-making processes, including the choice to migrate.

Table 7
Indirect effect on non-technical (migration) behavior.

Indirect effect	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Severity -> Migration	−0.022	−0.023	0.014	1.541	0.124
Self-efficacy -> Migration	0.011	0.009	0.011	1.034	0.301
Perception of others' behaviors -> Migration	−0.02	−0.02	0.016	1.245	0.213
Social capital -> Migration	−0.061	−0.06	0.027	2.211	0.027
Severity -> Migration	0.017	0.017	0.014	1.261	0.208
Benefits -> Migration	−0.02	−0.018	0.012	1.645	0.1
Barriers -> Migration	0.002	0.001	0.009	0.238	0.812
Attitude -> Migration	−0.006	−0.005	0.012	0.465	0.642
Moral norms -> Migration	−0.063	−0.062	0.03	2.078	0.038
Subjective norms -> Migration	0.026	0.026	0.018	1.454	0.146
Social discourse -> Migration	0	0	0.009	0.029	0.977

Empirical studies have demonstrated a significant relationship between perceived barriers and adaptive behaviors in agricultural contexts. For instance, Yazdanpanah et al. (2015) found that perceived barriers, such as financial constraints and lack of access to resources, were significantly associated with adopting adaptive measures among farmers facing water scarcity. This study illustrates how perceived barriers can shape farmers' responses to environmental stressors, including the decision to migrate to areas with better water access.

Consistent with these findings, the analysis reveals that perceived barriers (Beta=0.229, $P < 0.0001$) significantly influence non-technical adaptive behaviors, such as migration. In the context of migration behavior, perceived barriers can act as critical determinants. Phipps et al. (2013) showed that farmers' perceptions of the challenges posed by water salinity directly influenced their willingness to engage in non-technical adaptive behaviors. This finding aligns with the SCT framework, wherein perceived barriers decrease the likelihood of engaging in behaviors deemed difficult or unattainable.

Additionally, Rana and Dwivedi (2015) emphasized the role of perceived barriers in determining the effectiveness of outcome expectations in SCT. Their research indicated that even if farmers have positive outcome expectations regarding non-technical behaviors, high perceived barriers can dissuade them from taking action. This interaction between perceived barriers and outcome expectations underscores the complexity of migration decisions among farmers.

Therefore, integrating perceived barriers into the SCT model provides a more comprehensive understanding of farmers' migration behaviors in response to environmental challenges such as water salinity. The significant relationship between perceived barriers and migration behavior suggests that reducing these barriers can facilitate more adaptive responses among farmers.

The results also indicated that perceived benefits, within the framework of the ESCT, have a significant and positive effect (Beta=0.160, $P < 0.0005$) on farmers' intention to migrate. This suggests that if farmers perceive the potential benefits of migration—such as improved livelihoods, increased economic opportunities, and reduced dependence on saline water resources—they are more likely to adopt this adaptive strategy. In this regard, Tajeri Moghadam et al. (2020) stated that recognizing the benefits of adaptive behaviors can enhance individuals' intention to engage in such activities. The findings of this study further confirm that perceived benefits of migration constitute a key variable in farmers' decision-making processes when adapting to the challenges of water salinity. Previous studies have also highlighted the significant impact of this variable on behavioral intentions in various adaptation contexts (Shahangian et al., 2022; Yazdanpanah et al., 2015a; Boazar et al., 2020).

The present study also examined the impact of moral norms on farmers' migration intentions in response to agricultural well water salinity. The findings indicate that moral norms play a significant role in shaping farmers' behavioral intentions toward water resource conservation (Beta = 0.364, $P < 0.0001$). According to the results, a strong moral commitment to water conservation and, more broadly, technical adaptation measures can reduce farmers' likelihood of migration while increasing their willingness to adopt adaptive strategies. In many cases, water scarcity issues within communities are closely tied to ethical concerns, as some farmers do not perceive water resource conservation as a moral responsibility, which in turn influences their decision-making behavior.

Furthermore, previous studies have demonstrated that farmers with a conservation-oriented identity (CONID) exhibit a stronger commitment to protective behaviors compared to those with a production-oriented identity (PROID) (McGuire et al., 2013; Ives and Kendal, 2013; Valizadeh et al., 2020; Lequin et al., 2019). Farmers with a production-oriented mindset tend to prioritize maximizing the use of natural resources, whereas conservation-oriented farmers place greater emphasis on environmental values and the long-term sustainability of natural resources.

Therefore, incorporating moral norms into policy frameworks related to water resource management and reducing farmer migration is crucial. Strengthening these norms through education, outreach, and social engagement can enhance the adoption of conservation behaviors and reduce migration tendencies.

POB significantly influences farmers' migration decisions in response to well water salinity (Beta=0.358, $P < 0.001$). SCT posits that individuals learn not only through direct experience but also by observing the actions and outcomes of others' behaviors. This observational learning process is crucial in shaping farmers' perceptions of staying in their current location versus migrating (Bandura, 1986, 2001; Yazdanpanah et al., 2015; Thøgersen and Grønhøj, 2010).

Studies have shown that when farmers observe their peers successfully mitigating water salinity issues through innovative (technical) farming practices, they are more likely to adopt alternative strategies rather than migrate. Conversely, if the observed behavior among peers includes migration as a response to salinity stress, farmers are more likely to consider migration a viable option. This behavioral modeling can lead to collective movement, where entire communities might migrate, exacerbating the socio-economic impacts of environmental stressors like water salinity (Tinazzi, 2024; Uddin, 2024; Clech et al., 2023; Yazdanpanah et al., 2015; Pelling and High, 2005a).

Moreover, POB can be a critical factor in decision-making under environmental stress. If farmers perceive that their neighbors and peers cannot cope with salinity through local solutions and choose migration, this perception can create a sense of inevitability about migration. This aligns with findings that highlight the role of social actions and networks in environmental decision-making processes. POB acts as an essential mediator in the decision-making process of farmers, where the collective behavior of a community can either enhance the adoption of sustainable practices or initiate migration as an adaptive strategy. Considering this variable is emphasized for social and community-based intervention processes aimed at addressing environmental challenges like water salinity, ultimately strengthening resilience and reducing the necessity for migration (Ostrom, 2000; Emery and Flora, 2020; McLeman and Smit, 2006; Rodela, 2011; Adger, 2010).

Perceived sensitivity is a crucial component of the Protection Motivation Theory (PMT) and has been integrated into the Social Cognitive Theory (SCT) to enhance the understanding of behavior in various contexts, including environmental stressors such as water salinity (Rosenstock et al., 1988; Bandura, 2004). In the present study, this variable (Beta = −0.138, $P < 0.09$) represents an individual's cognitive evaluation of the likelihood and severity of negative consequences, such as the detrimental effects of saline water on crop performance and soil fertility.

Numerous studies have demonstrated the significant influence of perceived sensitivity on behavioral responses in agricultural settings. For example, research has shown that farmers who exhibit a heightened sensitivity to the negative impacts of water salinity are more likely to engage in adaptive behaviors, including migration (Yazdanpanah et al., 2014). This finding aligns with SCT, which posits that cognitive factors, such as risk perception, play a pivotal role in shaping behavioral intentions and subsequent actions (Bandura, 1986). Specifically, farmers who perceive themselves as vulnerable to water salinity are significantly more inclined to consider migration as an adaptive response to mitigate potential agricultural losses.

Pelling and High (2005a) further substantiated this relationship, demonstrating that perceived sensitivity serves as a strong predictor of non-technical adaptive behaviors among farmers facing severe water salinity challenges. Their findings highlight the necessity of incorporating cognitive factors, such as perceived risk, into predictive models of environmental adaptation behaviors (Pelling and High, 2005b). The integration of perceived sensitivity within the SCT framework provides a more comprehensive lens through which farmers' migration behaviors can be analyzed. As Bandura (2004) emphasized, perceived risk—when considered alongside other cognitive and environmental factors—enhances SCT's explanatory power in understanding complex adaptive behaviors, such as migration in response to environmental threats.

Thus, incorporating perceived sensitivity into the ESCT framework significantly enhances the theoretical understanding of farmers' migration behavior as a response to water salinity. Empirical evidence underscores the necessity of assessing both cognitive and environmental risks in shaping adaptive responses. Consequently, policymakers and planners should design interventions that address not only the objective risks associated with water salinity but also farmers' perceived vulnerabilities, ensuring more effective and targeted strategies for mitigating migration pressures in affected regions.

Incorporating the variable "perceived severity" into the SCT provides significant insights into "non-technical behaviors of farmers" in response to groundwater salinity. Research has demonstrated that perceived severity can be a critical determinant in influencing behavior, as it reflects an individual's assessment of the seriousness of the consequences of a specific issue, such as water salinity (Bandura, 1986). This cognitive evaluation can guide decision-making processes, particularly in stressful scenarios like water scarcity, encouraging farmers to consider migration a viable option (Yazdanpanah et al., 2015; Phipps et al., 2013). Consistent with these findings, the structural model results from this study further validate the importance of perceived severity, showing that it has a direct and significant impact on behavior (Beta=0.13, $P < 0.05$).

A study conducted by Thøgersen and Grønhøj (2010) explored the relationship between perceived severity and behavioral responses, revealing that higher perceived severity of environmental issues, such as water salinity, significantly correlates with an increased likelihood of undertaking drastic actions, including migration. This finding aligns with the premise that when farmers perceive the salinity problem as severe, they are more inclined to relocate to areas with better water quality to protect their livelihoods (Thøgersen and Grønhøj, 2010).

Moreover, empirical evidence from studies on agricultural communities indicates that perceived severity affects both intention and actual non-technical behaviors, such as migration. For instance, Keshavarz and Karami (2016) found that farmers who perceive water salinity as severe are more likely to engage in both technical and non-technical measures compared to those with lower perceived severity. This underscores the role of cognitive factors in shaping adaptive behaviors in response to environmental stressors (Keshavarz and Karami, 2016).

Incorporating "social discourse" into the Social Cognitive Theory (SCT) framework offers significant insights into farmers' migration behavior in response to water salinity. Social discourse, which encompasses community dialogues and public conversations, is essential in shaping both individual and collective perceptions regarding environmental challenges. This discourse impacts farmers' attitudes and behaviors by influencing their outcome expectations and self-efficacy, making it a critical element in the SCT framework.

When farmers engage in discussions about water salinity, they exchange important information and potential solutions, which significantly influence their decision-making processes concerning adaptation strategies, whether technical or non-technical (Bandura, 1986). Research has shown that strong social discourse within communities can mitigate the negative effects of environmental stressors by enhancing collective resilience and problem-solving capacities. As a result, the likelihood of migration decreases as farmers feel more capable of addressing challenges locally (Pelling and High, 2005a).

The impact of social discourse on migration behavior is further highlighted by its role in shaping outcome expectations. Farmers who perceive positive outcomes from collective adaptation efforts are less likely to migrate. Conversely, without robust discourse, negative outcome expectations may drive higher migration rates (Rana and Dwivedi, 2015). Empirical evidence supports these findings, showing that active community discussions on water management are linked to lower migration rates among farmers dealing with salinity issues (Yazdanpanah et al., 2015).

The significant negative influence of social discourse on migration behavior in this study (Beta= -0.149, $P < 0.05$) aligns with these observations, reinforcing its importance in reducing migration by fostering local resilience and adaptive capacity. Therefore, incorporating "social discourse" within the SCT framework provides a comprehensive understanding of farmers' migration behavior in response to water salinity. Strengthening robust social dialogues and support networks can thus reduce migration by enhancing local resilience and adaptive capacities.

Social capital, encompassing the networks of relationships within a community, plays a fundamental role in facilitating collective action and resource-sharing, particularly in response to environmental stressors such as water salinity. Within the framework of the ESCT, social capital exhibits a significant and positive association with migration intention (Beta $= 0.356$, $P < 0.0001$) and actual migration behavior (Beta $= 0.233$, $P < 0.0001$). These findings suggest that stronger social ties enhance access to information and resources, thereby influencing migration-related decision-making processes.

While high levels of social capital can strengthen community resilience and promote sustainable adaptation strategies, empirical evidence indicates that social networks can also facilitate migration. This occurs through financial support, information exchange, and connections to opportunities in destination areas. Households with strong horizontal social ties—such as mutual assistance among neighbors during environmental crises—are more likely to migrate due to greater access to mobility-enabling resources.

Moreover, studies have demonstrated that participation in community awareness programs and voluntary services is positively associated with migration behavior, as individuals embedded in well-connected communities often have better access to migration pathways. These findings underscore the dual role of social capital in shaping farmers' adaptive responses, as it can both reinforce local adaptation efforts and serve as a mechanism for facilitating migration as an alternative coping strategy.

Given the complexity of these interactions, policymakers should account for the multidimensional effects of social capital when designing interventions aimed at reducing migration pressures while enhancing community resilience. Strengthening local social cohesion through targeted initiatives—such as cooperative water management programs and shared infrastructure projects—can help mitigate the necessity of migration while simultaneously promoting sustainable agricultural practices in water-stressed regions.

6. Conclusion

In this study, the impact of various variables including perceived behavior of others, perceived sensitivity, attitudes, perceived barriers, and perceived severity within the framework of SCT were examined and derived from the PMT. The research employed the PLS-SEM method to evaluate a comprehensive model of factors influencing the non-technical behaviors of farmers. The findings indicated that all item loadings exceeded the minimum criterion of 0.7, and the CR ranged between 0.7 and 0.9, demonstrating good internal consistency of the constructs.

Given those non-technical behaviors (migration) of farmers is a critical issue that needs improvement in light of salinity and groundwater resource limitations, this study provides empirical evidence by examining influential factors and identifying the most impactful ones on farmers' non-technical behaviors in facing agricultural well water salinity issues. The results showed that factors such as perceived behavior of others, attitudes, and perceived barriers significantly impact the investigated behavior. Among these, the perceived behavior of others was identified as the most influential factor in the pro-migration behavior of farmers in the study area. Perceived benefits significantly influenced behavior indirectly, as indicated by a p-value below 0.1, demonstrating the most significant indirect effect with the highest t-statistic and lowest p-value among the evaluated paths.

The findings contribute both theoretically and practically to the study of migration behavior in response to agricultural water salinity. Theoretically, the results enhance the literature on the subject, highlighting the importance of the perceived behavior of others, attitudes toward relocation, and existing barriers, directly affecting the examined behavior and potentially serving as crucial factors for improving behavior assessment based on Social Cognitive Theory. The literature review indicates that the study of migration behavior in response to agricultural water salinity, particularly utilizing behavioral theories, is very limited. This study provides new knowledge, facilitating easier policy adoption or other assessments by identifying influential behavioral variables. Therefore, this study offers not only theoretical insights but also practical applications for various stakeholders involved.

Other examined variables also had different direct and indirect effects on farmers' behavior. Overall, the developed model could predict 48.4 % of the variance in intentions and 29.5 % of the variance in farmers' behavior. Ultimately, the results of this study suggest that strengthening social support networks and creating dynamic social discourses can increase local resilience and reduce the need for migration. Additionally, emphasizing cognitive factors in predictive models of adaptive behaviors can aid in more effective policy-making to mitigate the impacts of water salinity on agricultural communities.

Finally, it can be said that migration intentions are significantly shaped by self-efficacy, attitudes, perceived sensitivity, perceived severity, and social capital, with social capital and perceived severity exerting the strongest effects. While perceived barriers and perceived benefits play a notable role in migration intentions, social discourse has a minimal impact. Migration behaviors are directly influenced by migration intentions and social capital, though self-efficacy's direct effect remains weak. Additionally, perceived severity and perceived barriers significantly contribute to migration behaviors, whereas perceived benefits and sensitivity have limited influence. Lastly, social norms and discourse impact migration behaviors indirectly, primarily by shaping migration intentions, with moral and subjective norms demonstrating a strong predictive role.

This study has certain limitations that should be acknowledged. The findings are specific to farmers in Qaenat County, limiting their generalizability to other regions. Additionally, the cross-sectional design restricts causal inferences, suggesting that a longitudinal approach could provide deeper insights into behavioral changes over time. While Structural Equation Modeling (SEM) offers robust statistical analysis, it does not capture qualitative factors such as cultural influences and personal motivations, which may shape migration behaviors. Future research could address these gaps by adopting mixed-methods approaches and mitigating potential biases associated with self-reported data.

CRediT authorship contribution statement

Masoud Yazdanpanah: Validation, Supervision, Methodology. **Massoud Tabesh:** Writing – review & editing. **Seyyed Hamed Shakib:** Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Additionally, no conflicts of interest exist concerning the research, authorship, or publication of this article. All authors have approved the manuscript and agree with its submission to the journal.

Data availability

The data that has been used is confidential.

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