

Article

Investigating Farmers' Intentions to Reduce Water Waste through Water-Smart Farming Technologies

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Abstract: The scarcity of water resources, climate change, and water-wasting behavior have contributed to a worsening water crisis in many countries. This has raised concerns among farmers and increased pressure on governments. Digital technologies provide effective solutions to reduce resource waste; therefore, exploring farmers' willingness to implement water-smart farming technologies to reduce waste, especially in developing countries, requires further analysis. To address this gap, this paper aims to investigate the factors that influence farmers' intention to minimize water waste in Algeria. The theory of planned behavior was extended with the constructs of perceived usefulness of water-smart farming and knowledge of water waste reduction. Primary data were collected from 202 farmers to test the model. The empirical evidence suggests that attitudes, knowledge about water waste reduction, perceived usefulness, and perceived behavioral control significantly predict farmers' intention to reduce waste. These factors explained 54.6% of the variation in intention. However, social influence was not found to be a significant antecedent of intentions. This paper's findings can provide useful insights for various stakeholders on how to encourage farmers to reduce water waste and offer guidance on strategies for achieving sustainability in agriculture.

Keywords: perceived usefulness; smart water management; social marketing; sustainable agriculture; theory of planned behavior; waste management



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1. Introduction

Water is essential for all living organisms. However, water waste causes serious water shortages, which can exacerbate economic (such as food insecurity) and environmental (such as climate change) problems. The scarcity of water is a major issue that must be addressed in the XXI century [1–4], as it has led to a severe water crisis in many countries [5,6]. This has threatened food and water security and has caused migration and conflict [7]. Regarding this, Yazdanpanah et al. [8] stated that many countries, including those in North Africa, are seriously at risk of experiencing water shortages. They emphasized that reducing these risks requires focusing on the behavior of farmers. Similarly, Pino et al. [9] (p. 1) noted that “farmers represent a crucial target for water saving and efficiency policies”. In fact, “about 70% of the world's water is used for irrigation” [6] (p. 140). Agriculture “accounts for 69% of freshwater use on the planet” [10] (p. 1), which puts farmers at the center of any efforts to rationalize water consumption behavior. In the same vein, the literature suggests that the highest priority in resource management programs should be given to waste reduction, with recycling following closely behind [4,7,9,11]. Given that water is a crucial resource that must be conserved in farming, more attention should be paid to strategies that reduce water waste. To this end, the farming sector must take advantage of modern farming technologies to reduce water usage and waste while also seeking innovative solutions [12].

In practice, water waste reduction strategies include water conservation and savings [4,13,14], water recycling [11,15], water reuse [2], and reducing water use/consumption [16], among other measures. Therefore, it has become essential to encourage behaviors that reduce water waste as a solution to the water crisis. Indeed, farmers' voluntary actions to reduce water waste can be categorized into two types:

- Water waste avoidance behavior as traditional behavior of farmers (such as preventing water leakage), which is linked to awareness, knowledge, previous experience, and competence.
- Water waste reduction behavior using smart farming technologies as an innovative behavior of farmers, which is linked to the efficiency and ability of the farmers to acquire and use water-smart farming technologies.

In developing countries, such as Algeria, many farmers still use inefficient and unsustainable farming methods. The adoption of innovative technologies remains a challenging issue [17,18]. Although the Algerian government has made efforts to develop the agriculture sector and achieve sustainability in energy and water use [19], efforts to promote sustainable practices among farmers, particularly in the area of water conservation, require further attention. Chang et al. [13] argued that mandatory measures to reduce water use, such as "increasing irrigation water prices", along with voluntary measures such as adopting water-saving farming technologies, can help in "stringent water resource management", which may lead to reduced water waste. This can be achieved through smart farming technologies that help farmers manage their water resources more efficiently [20]. These technologies can also contribute to sustainable development goals by reducing water waste [6], minimizing water waste and saving water [21], reducing water use [10,12,22], and reducing costs while enhancing the efficiency of agricultural production [23]. It also contributes to sustainable farming [24] and the evaluation of multiple irrigation strategies [10]. Smart farming technologies "are smart devices parts of a cyber-physical system able to improve farm management" [25] (p. 1). The smart farming strategy focuses on using available technology to find effective solutions to various agricultural problems [26], one of which is related to water waste on farms. In practice, smart farming technology plays an important role in collecting sensor data, such as measuring "environmental temperature", "environmental humidity", "soil moisture", and "soil pH" [23], and this helps farmers manage various resources more effectively, which ultimately leads to reducing resource waste [22].

Although some studies have acknowledged the importance of considering the psychological and social aspects of farmers in providing valuable insights for stakeholders to help them design effective strategies for reducing water waste [8,11], the majority of previous studies have focused on technical aspects, such as the development of smart water systems for farming [10,12,22,27]. Ruzzante et al. [28] noted that despite the numerous benefits of adopting technology in farming, the adoption rate of these technologies remains low in developing countries. This is especially true in countries like Algeria, where research on water conservation behavior among farmers is limited. Therefore, there is a need to fill the gap in understanding the behavioral aspects of reducing water waste in farming through the adoption of various available smart farming systems.

Previous empirical studies have broadly adopted the theory of planned behavior (TPB) to investigate the determinants of waste reduction intentions and behaviors for various resources, such as energy [29,30] and water [9], and for different products, such as food [31,32], construction materials [33], and medicines [19]. Most of these studies have also expanded the TPB model by adding additional constructs and have confirmed that the extended model has a better predictive ability compared to the original TPB. For example, Yazdanpanah et al. [8] extended the TPB to investigate farmers' intentions and behaviors towards water conservation in Iran. Pino et al. [9] also adopted an extended version of the TPB to investigate the willingness of Italian farmers to adopt water-saving measures. They confirmed that attitude, subjective norms, and innovativeness are important predictors of intentions. Other studies have also found that factors like knowledge [31,33] and perceived

usefulness [34,35] can contribute to building positive attitudes towards reducing resource waste. This work extends the TPB by adding two new constructs: perceived usefulness of water-smart farming and knowledge related to reducing water waste. This goes in line with the call for further investigation into farmers' intentions to conserve water, as proposed by Valizadeh et al. [36].

Based on the above, this study aims to identify the factors influencing Algerian farmers' intention to reduce water waste using water-efficient farming techniques. This investigation contributes to answering the following three research questions:

- What is the effect of the TPB components (i.e., attitude, social influence, and "perceived behavioral control" (PBC)) on farmers' intentions to reduce water waste through water-smart farming technologies?
- What is the effect of additional constructs (i.e., perceived usefulness of water-smart farming and water waste reduction-related knowledge) on farmers' intentions to reduce water waste?
- Did the extended model improve the predictive power of the original TPB model?

Therefore, such research can help various stakeholders design effective measures to reduce water wastage in farming through the use of smart farming technologies. Furthermore, it can stimulate demand for these technologies and contribute to the achievement of sustainable agricultural goals. Additionally, it can "guide future social marketing efforts towards reducing water usage" [4] (p. 507).

The rest of this study is organized as follows: In the Section 2, the authors review the current literature and develop hypotheses. Section 3 describes the methodology and procedures. Section 4 presents the results. After that, in the Section 5, the authors discuss the contribution, managerial implications, and limitations of the study. Finally, Section 6 concludes the study.

2. Literature Review and Research Hypotheses

2.1. Smart Farming Technologies

Unsustainable farming practices and environmental pollution have contributed to climate change and a worsening performance of the farming sector in many countries [17,18,37]. In fact, several regions are experiencing water shortages due to various reasons, including water overuse, competition for water, and decreased rainfall caused by climate change [7,38]. At the same time, the demand for water for agriculture is increasing to meet the growing food needs of a growing population [20]. Under these challenging circumstances, it is essential to transition to "more sustainable agricultural systems" [7,39] and develop smart strategies for water conservation [20], especially since the adoption of innovative water-saving technologies is becoming increasingly common as a solution to the problem of water scarcity [1]. Chuang et al. [26] (p. 1) argued that "encouraging farmers to adopt digital technologies and mobile devices in farming practices has become a policy priority worldwide". Innovative methods for using water-smart technologies include floating agriculture, vertical farming, micro-irrigation, and deficit irrigation [21]. Accordingly, it is expected that smart farming technologies such as sensors, robotics, drones, and apps will be used to help farmers find sustainable solutions [26,40], including those related to reducing water waste in farming [7].

In practice, reducing water waste in irrigation is a major challenge faced by farmers in many countries. Adopting smart farming technologies can be a practical solution to this challenge [12]. According to Czekala et al. [41], the use of innovative digital technologies in waste management can help achieve sustainability goals. In recent years, there has been widespread interest in smart farming technology among policymakers, farmers, and researchers [10,20]. In this context, researchers have proposed several intelligent systems based on the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and/or cloud computing [3,12,16,27] to reduce water waste in various settings, such as farms, industries, cities, and universities. These systems have been shown to be effective in reducing water waste. For example, Jagtap et al. [16] reported that adopting an intelligent

water management system reduced excess water usage by 11%, while Morchid et al. [27] mentioned that their “proposed smart irrigation system” contributed to minimizing water consumption by 70%. Therefore, adopting these smart technologies has become not just an option but a necessary requirement for achieving sustainability, food security, and ensures effective water management.

2.2. Applying the TPB Model in the Context of Water Waste Reduction

Waste generation is directly linked to human behavior [41]. Therefore, any interventions aimed at reducing farming water waste that do not address farmers’ behavior may not produce the desired results. Waste reduction is a type of sustainable and environmentally friendly behavior [19]. It involves practices to reduce waste of various resources, such as water, food, medicines, and energy. This behavior can be influenced by several psychological and external factors. Therefore, it would be interesting to investigate farmers’ willingness to reduce water use, especially in the context of the widespread use of smart farming technologies.

The TPB assumes that human behavior is voluntary and rational and is influenced by intention, which is determined by three factors: attitudes, social influence, and PBC [42]. Behavioral intention is defined as “an individual’s expressed likelihood or willingness to engage in a specific behavior in the future” [43] (p. 5). Ajzen [42] (p. 181) argued that intention “capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior.” Regarding the gap between intention and actual behavior, many studies have confirmed that intention plays a significant role in predicting behavior in various contexts. For example, Mutyasira et al. [44] found that farmers’ intentions play a significant role in their adoption of sustainable agricultural practices in Ethiopia. Gibson et al. [45] also demonstrated that intention can predict water-saving behaviors in the United States. Moradnezhadi et al. [11] revealed that intentions to recycle water waste were positively correlated with farmers’ recycling behaviors in Iran, as confirmed by Su et al. [14] and Valizadeh et al. [36] in the context of water-saving among farmers in China and Iran, respectively. Therefore, predicting farmers’ intentions will help predict their actual behavior.

In their literature review, Sanchez et al. [46] asserted that the TPB is one of the most important theoretical frameworks used in studies investigating water conservation behavior. Several studies in the water literature have applied an extended version of TPB to investigate water waste recycling intentions, water-saving behavior, and water reduction among households, consumers [45,47,48], and farmers [11,36]. As TPB has become a leading model for explaining various sustainable behaviors, it is expected to be suitable for investigating water reduction behaviors among farmers. Additionally, extending the TPB with constructs, such as perceived usefulness and knowledge, is expected to enhance its predictive power.

2.3. Developing Research Hypotheses

2.3.1. Attitudes

Attitude was defined by Ajzen [42] (p. 188) as “the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question”. If farmers believe that using available farming technologies to reduce water waste is desirable and favorable, they are more likely to do so. People’s attitudes towards reducing waste can be influenced by various factors, such as personal norms, knowledge about waste minimization [33], perceived benefits [49], and awareness of consequences [13]. Previous studies have found that attitudes play an important role in intentions to reduce waste of food [31,32,49,50], energy [30], construction materials [33,51], and water [9,52]. Additionally, attitudes have been shown to be a significant predictor of farmers’ intentions to recycle farming water waste [11], and tourists’ attitudes have been found to predict their intentions to reduce waste as well [53]. The same results were found regarding intentions

to conserve water [45,47]. However, Warner and Diaz [4,48] emphasized that attitudes were not a significant predictor of water conservation intentions. Based on the assumptions of the TPB, it would be reasonable to expect that:

H1: *Attitudes have a significant influence on farmers' intentions to reduce water waste.*

2.3.2. Social Influence

Moussaïd et al. [54] (p. 1) defined social influence as “the process by which individuals adapt their opinion, revise their beliefs, or change their behavior as a result of social interactions with other people”. Based on this definition, farmers' views on practices to reduce water waste through smart farming technology could be influenced by social interactions with their peers. Skevas et al. [55] found that peer groups play a significant role in shaping farmers' adoption of new technologies like unmanned aerial vehicles. Previous studies have also shown that perceived social pressure can positively influence intentions to reduce waste [32–34,50,53] and conserve water [4,36,45,47,52]. For their part, Rasoulkhani et al. [1] noted that word of mouth, through social network interactions, may stimulate intentions to adopt water conservation technology. Li et al. [56] recently revealed that social norms play a significant role in the adoption of water conservation tillage technology among farmers. Based on the extended TPB model, Warner et al. [57] examined the behavior of encouraging others to save water and found that subjective and descriptive norms have an important influence on this type of behavior. Studies in the Algerian context have revealed that social influence positively contributes to influencing farmers' intentions to reduce energy consumption [19]. Yazdanpanah et al. [58], however, found that the effect of subjective norms on intentions to use renewable energy technology in Iran was insignificant. Chengqin et al. [49] revealed that social influence did not contribute to the formation of intentions to reduce food waste in Malaysia. Li et al. [51] reported the same result about intentions to reduce construction waste. Based on the above, the following hypothesis can be assumed:

H2: *Social influence has a significant influence on farmers' intentions to reduce water waste.*

2.3.3. Perceived Behavioral Control

Ajzen [42] (p. 183) defined PBC as “the person's perception of the ease or difficulty of performing a behavior of interest”. Accordingly, farmers' willingness to adopt water conserving practices using modern technologies depends on how difficult or easy these practices are to implement. Due to this, the availability of water-conservation devices serves as an external factor that encourages farmers to engage in these practices [46], while the costs associated with installing water-saving technologies act as a major barrier to their adoption [1]. Although many smart farming technologies are available at low costs, Lencsés et al. [59] noted that if farmers lack the capital to purchase new technologies, they may be unwilling to use them. Previous studies on waste reduction [19,32–34,50,51] and water waste recycling [11] have suggested the prominent role that PBC can play in shaping behavioral intentions. Recently, Warner et al. [57] revealed that PBC is the strongest antecedent of encouraging others towards water-saving behaviors. In the same vein, many studies have confirmed that PBC significantly drives water conservation intentions as a practice to reduce water waste [47,60]. However, some research has found that PBC may not be a significant antecedent for water conservation intentions [36,45,52]. Similarly, Chengqin et al. [49] found that intentions to reduce food waste are not influenced by PBC, and Pino et al. [9] demonstrated that PBC does not predict farmers' intentions to adopt measures to reduce water waste. Therefore, the authors propose the following hypothesis:

H3: *PBC has a significant influence on farmers' intentions to reduce water waste.*

2.3.4. Perceived Usefulness of Water-Smart Farming Technologies

Davis [61] (p. 320) defined perceived usefulness as “the degree to which a person believes that using a particular system would enhance his or her job performance”. In the context of this study, this refers to the farmer’s belief that using water-efficient farming techniques will reduce water waste and bring them certain benefits, such as reduced costs, increased productivity, and improved water use efficiency in farming. Direct communication between farmers can help them perceive the benefits of new farming technologies [55]. According to the economic paradigm, individuals are rational and seek to maximize their utility, so it is expected that farmers will form a perception of usefulness based on a cost-benefit analysis [61]. Smart farming systems rely on “a combination of hardware and software technologies for optimum benefits” [20] (p. 21219). Therefore, it is assumed that farmers’ adoption of farming technology is linked to maximizing economic benefits [28,62]. Xu et al. [63] found that economic incentives have a significant influence on farmers’ intentions to recycle pharmaceutical waste. Lazaridou et al. [15] confirmed that farmers’ willingness to use recycled water is linked to their perception of its environmental benefits. Additionally, previous research has shown that perceived usefulness is significantly associated with farmers’ willingness to adopt smart farming technologies [64–66]. Based on these findings, this study will test the hypothesis that:

H4: *Perceived usefulness of water-smart farming has a significant influence on farmers’ intentions to reduce water waste.*

2.3.5. Water Waste Reduction-Related Knowledge

Water waste management aims to manage water in a sustainable way. To achieve this goal, various techniques are used, such as water reuse, collection, and conservation [67]. According to Mirra et al. [5] (p. 1), “public awareness campaigns and education programs can instill water-saving habits”. Nevertheless, Jagtap et al. [16] (p. 1) found that “there is a lack of knowledge among food manufacturers about adopting the IoT-based water monitoring system and its ability to support water minimization activities”. Therefore, it is crucial for farmers to have knowledge about appropriate methods and practices for minimizing water waste. Farmers play a significant role in water conservation and must be aware of best practices to prevent water waste and reduce unnecessary water consumption. They also need to be familiar with smart farming technologies that can help minimize water waste and promote water conservation.

Several researchers have found that knowledge is related to farmers’ willingness to adopt new farming technologies [26,62] and reuse water [2], and this knowledge influences their intentions to implement sustainable farming practices [44]. Xu et al. [63] confirmed that information publicity positively influences farmers’ intentions to recycle pharmaceutical waste. Li et al. [56] found that technological cognition predicts farmers’ adoption of water conservation tillage technology. In their meta-analysis, Ruzzante et al. [28] found that the adoption of agricultural technology was associated with farmers’ education level. In the context of start-up medication waste collection projects, Njoku et al. [68] found that the intention to create such projects was influenced by knowledge about medication waste collection. According to Li et al. [33], knowledge about waste minimization is a strong predictor of construction waste reduction behavior. Akhter et al. [31] and Valentin et al. [32] found that knowledge about food waste significantly reduced food waste intention. Su et al. [14] found that knowledge about water conservation predicted farmers’ behavior to conserve water. In addition, several empirical studies have shown that lack of knowledge about waste management has a negative impact on effective waste management [69–71]. However, Thakur and Onwubu [72] found no significant relationship between waste management knowledge and awareness, TPB constructs, or waste management intentions in South Africa. Therefore, it would be reasonable to hypothesize that:

H5: *Water waste reduction-related knowledge has a significant influence on farmers' intentions to reduce water waste.*

3. Materials and Methods

3.1. Data Collection

In order to collect primary data and conduct empirical analysis, a self-administered paper questionnaire was distributed to a convenience sample consisting of 240 farmers in five agricultural towns in northern Algeria (Medea, Bouira, Djelfa, Ain Defla, and Tissemsilt). The questionnaire was administered over a three-month period, starting on 1 November 2023. The questionnaire was designed to gather information about the use of smart farming technologies by farmers in the region. Respondents were informed that their participation was voluntary, anonymous, and for scientific research purposes only. Respondents were interviewed at various locations, including their farms, shops selling agricultural equipment, and wholesale fruit and vegetable markets. It took approximately 8–12 min to complete the questionnaire. By the end of January 2024, the authors had collected 212 completed questionnaires. However, after checking the responses, the authors found that 10 of the questionnaires were incomplete, and 202 were eligible for empirical analysis.

3.2. Measurement of Constructs

As in many previous studies related to sustainable behavior [52,68], the authors relied on a self-reported questionnaire as a data collection tool. The authors also used a five-point Likert scale to measure responses, with a score of “1” indicating “completely disagree” and a score of “5” indicating “completely agree”. Three items were used to measure each of the six constructs included in the research model. Accordingly, all 18 questionnaire items were derived and adapted from previous investigations to fit the context of the current investigation. Based on this, the attitudes scale was derived from Mouloudj et al. [19], Bardus and Massoud [73], as well as Swarna Swetha et al. [74]. The social influence scale was adapted from Schrank et al. [50] and Qalati et al. [30]. Additionally, the PBC scale was drawn from Mouloudj et al. [19] and Wang et al. [53], and the perceived usefulness scale was obtained from Li et al. [66]. As for the water waste reduction-related knowledge scale, it was modified from the scales used by Njoku et al. [68] and Zhang et al. [75]. Finally, farmers' intentions to reduce water waste were measured using a scale adapted from Borusiak et al. [76] and Mouloudj et al. [19]. In addition to the measurement tool, the questionnaire collected some demographic information about the respondents, including their gender, age, education level, and monthly income. After completing the questionnaire development process, the authors invited three experts to review its content and identify any potential issues. As a result of this process, the authors made some simple changes, such as replacing certain words with more common ones. Then, the authors hired two professional translators to translate the questionnaire from English (the original language) into Arabic (the mother tongue of respondents), using the back-translation method to ensure high-quality translations. In the next step, the authors conducted a pilot study with 15 farmers to ensure that the questionnaire questions were clear and understandable. The final version of the survey questionnaire is presented in Table 1.

Table 1. Constructs and statements.

Constructs	Code	Statements	Code	References
Attitudes towards reducing water waste through smart farming technologies	AT	I believe that reducing water waste through smart farming is a wise and economical behavior	AT1	Mouloudj et al. [19], Bardus and Massoud [73]; Swarna Swetha et al. [74]
		I believe that reducing water waste through smart farming is environmentally responsible behavior	AT2	
		I think that reducing water waste through smart farming is a good ethical behavior	AT3	

Table 1. Cont.

Constructs	Code	Statements	Code	References
Social influence	SI	My colleagues think that I should reduce water waste	SI1	Schränk et al. [50]; Qalati et al. [30]
		Most people whose opinions I value want me to reduce water waste	SI2	
		If I reduce water waste through smart farming, the people important to me will encourage this behavior	SI3	
Perceived behavioural control	PBC	I am confident that I can reduce water waste by adopting smart farming technology	PBC1	Mouloudj et al. [19]; Wang et al. [53]
		I have the resources and opportunities to reduce water waste by adopting smart farming technology	PBC2	
		I believe I am capable of reduce water waste by adopting smart farming technology	PBC3	
Perceived usefulness of water-smart farming	PUWSF	Using water smart farming technologies is useful for conserving water resources	PUWSF1	Li et al. [66]
		Using water-smart farming techniques can reduce costs and enhance my productivity	PUWSF2	
		Using water-smart farming technologies can reduce unnecessary water consumption	PUWSF3	
Water waste reduction-related knowledge	WWRK	I know how to reduce water waste through smart farming properly	WWRK1	Njoku et al. [68]; Zhang et al. [75]
		I have sufficient knowledge of water collection and reuse technologies	WWRK2	
		I have adequate knowledge of water conservation technology	WWRK3	
Intention to reduce water waste	IRWW	I plan to reduce water waste through smart farming in the future	IRWW1	Borusiak et al. [76]; Mouloudj et al. [19]
		I am willing to reduce water waste through smart farming	IRWW2	
		I will do my best to reduce water waste through smart farming	IRWW3	

Source: authors' development.

3.3. Data Analysis

Primary data were analyzed using SPSS software (Version 26.0, IBM, Armonk, NY, USA). In this work, mean scores and standard deviation values were considered, along with the correlation matrix, to discover the nature of the relationships between the model's constructs. Additionally, Cronbach's alpha coefficients were calculated to check reliability. The skewness and kurtosis tests were also used to ensure that the data followed a normal distribution [68]. Furthermore, the variance inflation factor (VIF) and tolerance tests were employed to address the issue of multicollinearity. Next, following the studies of Njoku et al. [68] and Russell and Knoeri [52], hierarchical regression analysis was used to test the hypothesized relationships between antecedents and farmers' intentions, confirming the feasibility of adding additional lenses to the original TPB model.

4. Results

4.1. Sample Characteristics

Regarding the demographic data (Table 2), all respondents were male (100%). As for the age group, 36.14% were aged between 41 and 50 years, 28.71% were between 31 and 40, and 22.77% were over 50 years. With regard to education, 44.06% had a high school education or less, 26.73% had a vocational diploma, and 20.79% had a tertiary degree. Considering monthly income, 36.63% of the respondents earned between DZD ((Algerian dinars) 50,000 and 75,000), 31.19% between DZD 75,001 and DZD 100,000, and 21.78% earned less than DZD 50,000. In terms of farming experience, nearly half (55.45%) of the respondents have been engaged in farming for more than 10 years, while the other half (44.55%) have less than 10 years. Finally, most respondents (75.74%) lived in rural areas.

Table 2. Demographic data of respondents ($N = 202$).

Variables	Items	Frequency	Percentage
Gender	Male	202	100
	Female	-	-
Age	18–30 years old	25	12.38
	31–40 years old	58	28.71
	41–50 years old	73	36.14
	>50 years old	46	22.77
	High school level or less	89	44.06
Education level	Vocational training diploma	54	26.73
	Tertiary (Diploma/bachelor’s degree)	42	20.79
	Postgraduate (Masters/PhD)	17	8.42
Monthly household income	<50,000 DZD	44	21.78
	50,000–75,000 DZD	74	36.63
	75,001–100,000 DZD	63	31.19
	>100,000 DZD	21	10.40
Experience in farming work	<5 years	42	20.79
	5–10years	48	23.76
	11–15 years	67	33.17
	>15 years	45	22.28
Residence area	Rural areas	153	75.74
	Urban areas	49	24.26

Source: authors’ development.

4.2. Descriptive Statistics Analysis of Results

The results indicate that farmers have a positive attitude and a strong desire to reduce water waste, with mean scores of 3.97 and 3.50, respectively. However, their PBC was low, with a mean of 2.63. Additionally, social influence, perceived usefulness, and knowledge about water waste reduction received moderate scores, with averages of 3.30, 3.33, and 3.11, respectively. Therefore, these results suggest the need to enhance PBC and perceived usefulness, in addition to improving the level of farmers’ knowledge related to reducing water waste using digital technologies. According to Hair et al. [77], if Cronbach’s alpha coefficients are greater than 0.7, the questionnaire can be considered reliable. Table 3 shows that the Cronbach’s alphas ranged between 0.749 for PBC and 0.935 for perceived usefulness, indicating that the questionnaire has good reliability.

Table 3. Descriptive statistics, Cronbach’s alphas, and correlation matrix.

Constructs	AT	SI	PBC	PUWSF	WWRK	IRWW
AT	-					
SI	0.592 **	-				
PBC	0.315 **	0.253 **	-			
PUWSF	0.806 **	0.631 **	0.325 **	-		
WWRK	0.419 **	0.506 **	0.414 **	0.402 **	-	
IRWW	0.672 **	0.551 **	0.385 **	0.662 **	0.509 **	-
Cronbach’s Alphas	0.870	0.922	0.749	0.935	0.757	0.815
Mean	3.97	3.30	2.63	3.33	3.11	3.50
Standard deviation	0.69	0.67	0.45	0.73	0.54	0.61
Skewness	−1.23	−1.10	−0.211	−1.13	−1.12	−1.40
Kurtosis	1.40	1.41	0.72	1.02	1.79	2.44

Note: ** correlation is significant at the 0.01 level (2-tailed); AT = attitudes; SI = social influence; PBC = perceived behavioral control; PUWSF = perceived usefulness of water-smart farming; WWRK = water waste reduction-related knowledge; IRWW = intention to reduce water waste. Source: authors’ development.

As for the correlation between the constructs of the study model, the results of Table 3 indicate that intentions to reduce water waste were positively and strongly correlated with attitudes ($r = 0.672$, $p < 0.01$) and moderately correlated with social influence ($r = 0.551$, $p < 0.01$), perceived usefulness ($r = 0.662$, $p < 0.01$), and water waste reduction-related

knowledge ($r = 0.509, p < 0.01$). However, the association between farmers' intentions and PBC was positive but relatively weak ($r = 0.385, p < 0.01$). Hence, these results suggest that any interventions aimed at enhancing attitudes, social norms, perceived usefulness, and knowledge will improve farmers' intentions to engage in water waste reduction. It is also expected that overcoming the challenges associated with this behavior will lead to the formation of stronger intentions.

As for the normal distribution, skewness and kurtosis are commonly used statistical tests to check the normality of the data set [68]. Therefore, Table 3 shows that the skewness degrees ranged between -1.40 and -0.21 , which fell within the range from -2 and $+2$, while the kurtosis degrees ranged between 0.72 and 2.44 , which fell within the range of -7 and $+7$; this means that the data followed a normal distribution [68].

4.3. Testing Research Hypotheses

In order to understand the predictive power of the extended TPB model compared to the original version, the authors conducted a hierarchical multiple regression analysis. Three models were considered: Model 1 included only the constructs of the original TPB; Model 2 added the perceived usefulness construct; and Model 3 incorporated the expanded TPB with additional constructs related to perceived usefulness and water waste reduction knowledge.

Conducting hierarchical multiple regression analysis requires ensuring that “there is no multicollinearity issue” in the data [68]. Therefore, VIF and tolerance tests can be used to check this issue [68]. Table 4 shows the results of these tests for the three models. The tolerance values ranged between 0.31 and 0.89 , which exceeds the threshold of 0.2 . The VIF indices ranged between 1.11 and 3.21 and were less than the threshold of 5 . This indicates the absence of multicollinearity in the models, as confirmed by Hair et al. [77].

Table 4. Hierarchical regression analysis results.

Models	Constructs	B	t	Sig	Tolerance	VIF	F (Adjusted R ²)
Model 1	(constant)	0.492	2.198	0.029			
	AT	0.432	7.759	0.000	0.620	1.613	F = 70.232 ($p < 0.001$); (R ² = 0.508)
	SI	0.201	3.541	0.000	0.645	1.551	
	PBC	0.239	3.366	0.001	0.894	1.119	
Model 2	(constant)	0.583	2.620	0.009			
	AT	0.295	3.962	0.000	0.337	2.970	F = 56.260 ($p < 0.001$); (R ² = 0.524)
	SI	0.150	2.555	0.011	0.581	1.722	
	PBC	0.219	3.119	0.002	0.884	1.131	
	PUWSF	0.202	2.732	0.007	0.311	3.214	
Model 3	(constant)	0.390	1.728	0.085			
	AT	0.272	3.719	0.000	0.333	2.999	F = 49.311 ($p < 0.001$); (R ² = 0.546)
	SI	0.084	1.370	0.172	0.515	1.941	
	PBC	0.144	1.990	0.048	0.794	1.259	
	PUWSF	0.208	2.886	0.004	0.311	3.216	
	WWRK	0.220	3.252	0.001	0.648	1.543	

Note: AT = attitudes; SI = social influence; PBC = perceived behavioral control; PUWSF = perceived usefulness of water-smart farming; WWRK = water waste reduction-related knowledge. Source: authors' development.

The results of Model 1, summarized in Table 4, show that attitude ($\beta = 0.432, p < 0.001$), social influence ($\beta = 0.201, p < 0.001$), and PBC ($\beta = 0.239, p < 0.01$) positively and significantly influenced farmers' intentions to reduce water waste by adopting smart farming technologies. These three TPB constructs contributed to 50.80% of the variance in farmers' intentions in this model. The results of Model 2 also show that attitude ($\beta = 0.295, p < 0.001$), social influence ($\beta = 0.150, p < 0.05$), PBC ($\beta = 0.219, p < 0.01$), and the perceived usefulness of water-smart farming technologies ($\beta = 0.202, p < 0.01$) positively and significantly influenced farmers' intentions to reduce water waste through the use smart farming technologies. In Model 2, combining the perceived usefulness construct with the TPB

constructs contributed to explaining 52.40% of the variance in farmers' intentions, which indicates an improvement in the predictive ability of the model by 1.60%.

In addition, the results from Model 3 (as shown in Figure 1) indicate that attitude ($\beta = 0.272, p < 0.001$), PBC ($\beta = 0.144, p < 0.05$), perceived usefulness ($\beta = 0.208, p < 0.01$), and water waste reduction-related knowledge ($\beta = 0.220, p < 0.01$) all significantly and positively influence farmers' intentions to reduce water waste using smart farming technologies. Therefore, hypotheses H1, H3, H4, and H5 are supported. In contrast, social influence did not significantly affect farmers' intentions ($\beta = 0.084, p = 0.172$), suggesting that the availability of knowledge about water waste reduction methods through smart farming may reduce the influence of social factors.

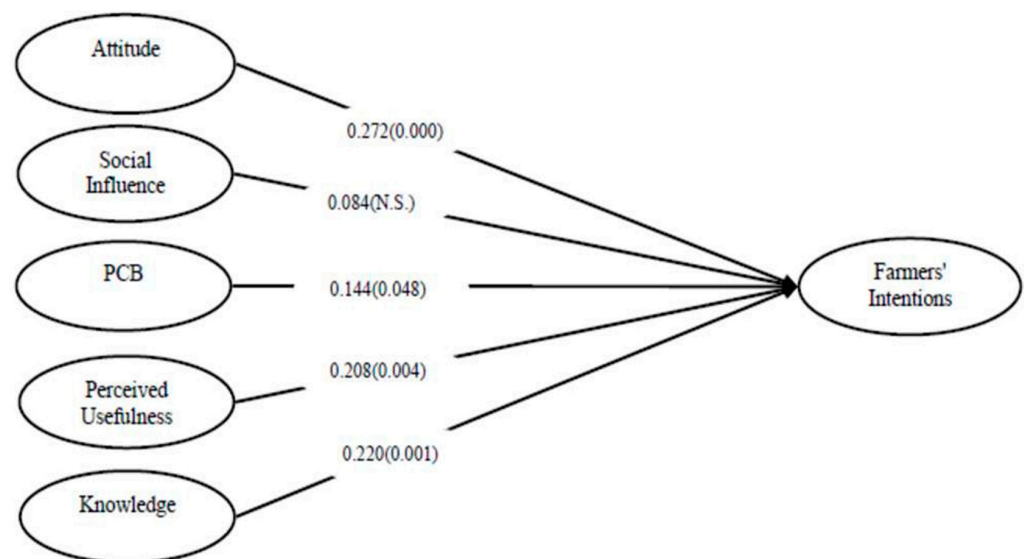


Figure 1. Hierarchical multiple regression results for the extended TPB model (Model 3). Note: N.S. = not significant.

In Model 3, the incorporation of both perceived usefulness and water waste reduction-related knowledge, together with the TPB constructs, contributed to explaining 54.60% of the variance in farmers' intentions. This means that the inclusion of knowledge related to water waste reduction improved the ability to predict farmers' intentions by up to 2.20%. Therefore, the authors conclude that the extended model contributed to enhancing the predictive power of the original TPB model by 3.80%. Moreover, additional constructs, namely knowledge ($\beta = 0.220$) and perceived usefulness ($\beta = 0.208$), constituted the second and third strongest predictors of farmers' intentions, respectively, after attitudes. Nevertheless, these results indicate that about 45% of the variance in farmers' intentions is explained by other factors not included in our model. In fact, human behavior is influenced by many internal and external factors, in addition to contextual and situational factors, which makes its prediction difficult and complex. Accordingly, it may be useful to extend the TPB model with additional constructs from other psychological theories or models.

5. Discussions, Implications, and Limitations

5.1. Discussions

Various practices to reduce water waste, such as environmentally friendly behaviors, can play an effective role in addressing the problem of water scarcity and achieving the Sustainable Development Goals (SDGs), especially SDG 6, which focuses on ensuring the availability and sustainability of water resources [2,7]. In this study, the authors aimed to understand the factors that motivate farmers to reduce water waste through the use of water-efficient farming technologies in Algeria. To do so, the expanded version of TPB was proposed, which includes two additional constructs: perceived usefulness and water waste

reduction-related knowledge. For this, five hypotheses were tested. The empirical analysis showed that four hypotheses (H1, H3, H4, and H5) were supported, while H2 was not supported. So, our results not only provide significant contributions to the field of water waste management but also provide valuable guidance to various stakeholders on how to motivate farmers towards adopting water waste reduction behaviors.

The empirical evidence demonstrates that positive attitudes are significantly correlated with intentions to reduce water waste. This finding suggests that favorable attitudes towards reducing water waste through the adoption of smart farming technologies can influence farmers' willingness to engage in behaviors that reduce water waste. This result provides empirical support for the findings of Pino et al. [9], who reported that attitudes play a significant role in shaping farmers' intentions to implement water waste reduction measures. Additionally, this finding is consistent with several other studies that have found a positive correlation between attitudes and willingness to save water [36,45,47,52] and reduce resource waste [11,31–34,49,53,57]. These findings suggest that it is important to foster positive attitudes among farmers towards various water conservation practices using digital technologies in order to enhance their willingness to implement these practices. On the other hand, it is important to work towards changing any negative attitudes that might arise from misunderstandings, lack of knowledge, or traditional agricultural practices that are not sustainable.

The study also confirms that knowledge related to water waste reduction has a positive effect on intentions to reduce waste. This suggests that farmers who are knowledgeable about waste reduction methods will be more likely to engage in them compared to those without this knowledge. This makes sense, as people's attitudes and behaviors are influenced by their level of understanding of an issue. Mutyasira et al. [44], Fahad et al. [78], and Mashi et al. [79] have argued that the adoption of sustainable farming practices can be facilitated by increasing farmers' awareness. Ricart and Rico [2] found that knowledge is a key determinant of farmers' willingness to recycle water. Xu et al. [63] (p. 2870) reported that "information publicity can exert an indirect effect on recycling intention through subjective norms". This finding is supported by previous research, as a positive relationship between knowledge and behavioral intentions has been demonstrated in empirical studies [26,68,74], including studies on waste reduction intentions and behaviors [14,31–33]. This result emphasizes the importance of focusing on improving farmers' knowledge of water waste reduction practices using digital technologies.

Furthermore, the empirical results validate the positive effect of PBC on farmers' intentions to reduce water waste. This suggests that PBC can predict farmers' willingness to adopt water-saving practices through the use of smart farming technologies. Morad-nezhad et al. [11] found that barriers are negatively associated with farmers' intention to recycle water waste. Rasoulkhani et al. [1] indicated that consumers' adoption of water-conservation technology depends on various factors, including the ability to afford the technology. This implies that the high cost of digital technologies to reduce water waste may hinder their adoption. In practice, barriers to implementing irrigation water waste reduction measures can include internal factors (e.g., a lack of knowledge about how to conserve water) and external factors (e.g., limited access to systems that reduce excessive water use) [4]. Therefore, it is essential for stakeholders to identify the nature of these obstacles in order to find solutions. Large farmers, on the other hand, are more likely to adopt smart water technologies to reduce water wastage due to their experience and financial constraints (capital). It would therefore be beneficial to assist smallholders in overcoming any obstacles that limit their ability to implement water waste reduction systems. This finding is consistent with the results of several studies that have revealed a significant relationship between PBC and waste reduction intentions [31,32,34,50,53,74]. These findings also support the results of numerous studies related to the intention to implement environmentally friendly practices, such as recycling water waste [11], conserving water and energy [4,19,47], and sorting waste [73]. This result emphasizes the importance of

focusing on overcoming any obstacles that farmers may face while implementing water waste reduction practices using digital technologies.

In addition, the results confirmed that the perceived usefulness of water-efficient farming contributes to the formation of intentions to minimize water waste. Davis [61] (p. 320) stated that “people tend to use or not use an application to the extent they believe it will help them perform their job better”. Therefore, it is expected that improving farmers’ perception of the benefits of water-saving farming will lead to stronger positive intentions to reduce water wastage. From an economic perspective, the use of these technologies has several benefits, including improved water use efficiency, reduced volume of water wasted, and, in turn, reduced costs associated with irrigation (water, energy, and supplies), reduced effort for irrigation workers, and improved farm profitability. From an environmental perspective, the use of this technology undoubtedly contributes to enhancing agricultural sustainability. This finding is consistent with previous studies that have found a positive relationship between intentions to use innovative smart farming technologies and perceived usefulness [64–66]. In addition, a recent study by Zhang et al. [35] found that perceived corporate social responsibility (CSR) value plays a mediating role in the relationship between intentions to reduce food waste and actual behavior. Furthermore, according to the Technology Acceptance Model (TAM), perceived usefulness is a key factor influencing intentions to adopt new technologies [61]. This result underscores the importance of focusing on improving farmers’ perceived usefulness levels.

Finally, the authors’ results indicate that social influence was not a significant predictor of farmers’ intentions to reduce water waste. Although our extended model (Model 3) demonstrated that social influence does not significantly predict water waste reduction intentions, the original TPB model (Model 1) revealed the influence of this construct along with attitudes and PBC. In the same way, Warner and Diaz [4] found that incorporating personal norms into the TPB substantially reduced the effect of social pressure on water conservation intentions. One possible explanation for this finding is that farmers with sufficient knowledge may not rely on the information available to others. This is supported by the idea that the need for external information increases when individuals lack knowledge, experience, or personal skills. Conversely, when individuals have sufficient knowledge and skills, they may be less likely to rely on external sources of information. This finding aligns with the results of Moradnezhadi et al. [11], who found no significant relationship between subjective norms and farmers’ intentions to recycle water waste. Similarly to the findings of Yazdanpanah et al. [58] regarding intentions to use renewable energy technologies in Iran, it is important to consider the relative importance of different factors that influence these intentions. Ajzen [42] noted that in some situations, attitudes and perceived behavioral control are sufficient to form intentions, meaning that in certain behaviors, social pressure may not significantly influence individuals’ intentions. However, other research has found that social pressure can be an important factor in promoting waste reduction intentions [19,32,34,53] and the adoption of water conservation technologies [1]. This suggests that the impact of social pressure may vary depending on cultural, social, and contextual factors. In a similar vein, Njoku et al. [68] argued that the degree to which social pressure influences intentions to engage in environmentally friendly behaviors depends on factors such as educational level and “the perception of information quality provided by members of reference groups” [68] (p. 13). In addition to the above, social norms, such as those of peers and friends, constitute an important source of information about farming techniques [56]. This information plays a significant role in the early stages of the development of new farming technologies, but its importance decreases in later stages [55]. This is further evidence of the varying role that social pressures can play in promoting sustainable practices based on the digital technology life cycle.

5.2. Managerial Implications

Reducing water waste is the responsibility of everyone and is essential for achieving sustainable management of water resources [80]. This study builds on and extends

existing literature on water waste reduction behavior from the perspective of farmers, using water-smart farming technologies. It provides insights for various stakeholders, such as the Ministry of Water Resources, the Ministry of Agriculture, provincial agricultural directorates, dam managers, farmer unions, and environmental protection associations, to help them design effective strategies aimed at preventing water waste in farming. To achieve this goal, policymakers need to employ social marketing strategies to maximize the benefits.

First, it is important to increase farmers' positive attitudes towards reducing water waste. This requires understanding the factors that influence these attitudes, such as analyzing negative beliefs about water waste reduction practices and providing farmers with information to strengthen their positive attitudes [13]. Stakeholders should also work to reduce negative attitudes by educating farmers about the environmental and economic costs of wasting water. By raising awareness of the risks of water shortages and the economic consequences of wasting water, farmers will be more likely to adopt positive behaviors. Additionally, religious values that emphasize the importance of preserving water resources can be used to encourage farmers to feel morally responsible for conserving water.

Second, knowledge (technical and administrative) related to practices for reducing farming water waste should also be enhanced. This includes knowledge about how to use available apps to monitor excess water consumption and water-saving devices. It would be beneficial to target farmers through various social marketing programs aimed at sharing this knowledge. For example, educational videos could be posted on social media platforms, TV programs could be created with experts in this field, and farmers could receive specialized publications (books, leaflets, posters) that explain the targeted practices with illustrations that take into account their level of understanding.

Third, increasing farmers' awareness of the benefits of using smart technologies to reduce water waste, especially economic benefits such as reduced irrigation water costs, is essential. Therefore, addressing farmers using language that includes numbers and statistics is expected to contribute to improving their understanding of the benefits that they can gain from adopting smart water technology. For example, farmers can be provided with information on the amount or ratio of water that is saved or the amount of money that can be saved as a result of using different alternative smart irrigation systems. This information is expected to help improve the perceived usefulness of these technologies and encourage farmers to choose the best alternatives for their needs.

Fourth, enhancing farmers' perception of their self-efficacy and ability to implement water conservation practices through the adoption of smart farming technologies is a key task. In fact, it will be challenging to design an effective program to promote water conservation behaviors without prior knowledge of the barriers to implementation of these behaviors [4]. Therefore, PBC could be enhanced through irrigation engineers and experts visiting farms to meet with farmers face-to-face in order to answer their questions and concerns related to water conservation; simplify the implementation of these practices; provide farmers with information about programs, suppliers, water reduction systems, and programs and their costs; and assist farmers in installing and using water-saving devices and systems for agriculture. Furthermore, highlighting other farmers' successful experiences can help increase farmers' confidence in their abilities. In addition, farmers' PBC could be enhanced by creating a sense of encouragement, support, and accompaniment from the authorities. The authorities should demonstrate their readiness to intervene in case of any difficulties that farmers may encounter while implementing water waste reduction measures.

Fifth, although the inclusion of knowledge related to water waste reduction practices in the extended model (Model 3) reduced the role of social influence on farmers' intentions to reduce water waste, the role of reference groups and opinion leaders should not be ignored, as they could play a significant role in providing reliable information and advice that can contribute to creating awareness of the need to reduce water consumption and build positive attitudes towards waste reduction, especially among farmers who lack

knowledge about the benefits of reducing farm water waste. Therefore, it is important to employ subjective norms, such as peer farmers, agronomists, clergy, agricultural experts, and influencers, as communication channels for passing various advertising messages.

Finally, concerning expanding the use of various smart farming technologies in the farming sector, the concerned authorities should develop a clear business strategy for integrating digital technology into various farming activities, taking into account the specificity and background of the farmer segment. In this regard, several initiatives could be taken, such as:

- Providing the latest technologies at affordable prices.
- Recruiting a technical staff including agricultural engineers and experts to guide and accompany the transformation processes towards integrating digital technology in the field of farming.
- Forming a specialized cell to monitor the implementation of this strategy to identify any obstacles (financial, managerial, organizational, political, or legal) that may prevent the achievement of the desired goals.

5.3. Limitations and Future Research

Although the current study makes useful contributions to managing farm water waste, there are some limitations that limit the generalizability of its findings in other cultural and economic contexts.

First, the current study used an extended version of the TPB, and it is expected that by applying other theories, one can expand current knowledge of farming water waste reduction behaviors. For instance, future studies could use the Technology Acceptance Model (TAM), Value-Belief-Norm (VBN), and Norm Activation Model (NAM) to better understand farmers' intentions. Additionally, the authors' extended model explains about 54% of the variation in farmers' intentions, so including more variables within the TPB would increase the accuracy of predictions regarding farmers' intentions. Future investigations could also include religious values, moral values, and perceptions of environmental responsibility within the TPB or another behavioral model to gain a more comprehensive understanding of farmers' behavior.

Second, this study focused solely on examining psychological factors, but undoubtedly, contextual, demographic, social, and cultural factors also play a significant role in predicting farmers' intentions to reduce water waste in agriculture. Therefore, it would be beneficial to include these factors within a comprehensive model in order to gain a better understanding of water conservation behavior on farms.

Third, this study focused on the determinants of water waste reduction, without exploring the obstacles to implementing water-saving behaviors through the adoption of agricultural technologies, especially those associated with the use of digital technology by farmers. Analyzing these obstacles may help increase the ability to overcome difficulties in implementing sustainable farming practices based on innovative technologies.

Finally, the current study focused on farmers' intentions to reduce water waste through the use of smart farming technologies, without addressing other forms of waste on farms, such as energy waste, fertilizer waste, and agricultural product waste. Therefore, exploring intentions to implement various smart farming techniques to reduce, recycle, or reuse agricultural waste could be an interesting area of research. Additionally, it would be beneficial to fill knowledge gaps related to water waste reduction through the use of digital technology in other sectors, such as industrial companies, hotels, households, laundries, and showers.

6. Conclusions

Many countries suffer from water waste in farming, so it has become necessary to adopt a more sustainable approach to farming. Therefore, the main objective of this investigation was to examine farmers' intentions to minimize waste through the use of smart farming technologies. The authors extended the TPB model by including two

additional constructs: perceived usefulness and knowledge of water waste reduction. Based on a self-reported questionnaire from 202 farmers, the study found that attitudes towards water waste reduction, knowledge about water-saving farming technologies, PBC, and other factors were significant drivers of farmers' intentions to reduce water waste in their farming practices. The results also showed that the extended version of the TPB model explained 54.60% of the variation in farmers' intentions, an increase of 3.80% compared to the original model. This suggests that including additional factors in behavioral models can help explain more complex behaviors. However, social influence was not found to significantly affect farmers' intentions when knowledge was included in the model. These findings could be useful for policymakers and other stakeholders who want to promote water conservation in agriculture. Furthermore, the findings of this study are anticipated to encourage scholars to broaden their discussions on ways to achieve water sustainability in farming in the era of smart agriculture.

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