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FARMERS' ADOPTION OF SMART AGRICULTURE AND SMART IRRIGATION IN IRAQ: AN EXTENDED TECHNOLOGY ACCEPTANCE MODEL WITH HUMAN-CAPITAL ANTECEDENTS

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Abstract. *Water scarcity is pushing Iraqi agriculture towards smart irrigation and sensor-based farm management, yet adoption by smallholders remains low. This study examines how farmers' human capital, namely digital literacy and access to agricultural extension and training, shapes the adoption of smart agriculture technologies. An extended Technology Acceptance Model (TAM) is proposed in which digital literacy and extension support act as antecedents of perceived ease of use and perceived usefulness, alongside social influence and perceived cost and risk. Data from a structured survey of 386 farmers in Babylon, Karbala, Al-Qadisiyah and Wasit provinces were analysed with partial least squares structural equation modelling (PLS-SEM). The measurement model met all reliability and validity criteria, and all twelve hypothesised paths were significant. Behavioural intention was the strongest driver of actual adoption ($\beta = 0.47$), and perceived usefulness the strongest driver of intention ($\beta = 0.31$). Digital literacy had the largest effect on perceived ease of use ($\beta = 0.40$) and influenced intention only indirectly, through ease of use and usefulness. Extension support affected every stage of the model and had the largest total effect on adoption (0.22), whereas perceived cost and risk reduced intention ($\beta = -0.18$). The model explained 35% of the variance in intention and 27% in adoption. Investment in farmers' digital skills and in a digitally capable extension service is therefore a precondition for the uptake of smart irrigation, and agricultural water policy and rural human-development policy in Iraq should be designed together.*

Keywords: *smart agriculture; smart irrigation; technology acceptance model; digital literacy; agricultural extension; PLS-SEM; Iraq*

1. INTRODUCTION

Iraq faces an escalating water crisis. Flows in the Tigris and Euphrates have declined because of upstream dam construction and climate change, while agriculture, the largest water user, still relies mainly on surface flood irrigation with low conveyance and field efficiencies; the overall efficiency of the western canal of the Al-Ishaqi irrigation project, for example, has

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been estimated at only 28.3% [1]. Smart farming technologies, including soil-moisture sensors, IoT-based irrigation controllers, scheduled drip and sprinkler systems and mobile advisory applications, can reduce water use without lowering yields. Nevertheless, their adoption by Iraqi farmers remains limited.

Technology adoption in agriculture is not only an engineering or economic question; it depends on the people expected to use the technology. Farmers' education, digital skills and access to advice shape how useful and how easy to use they perceive a technology to be, and hence their willingness to invest in it [2]. Recent reviews and surveys confirm that technical knowledge, infrastructure and the perceived usefulness of digital tools are among the main drivers of, and barriers to, digital agriculture adoption [3,4]. Adoption is therefore also a human-development issue, since rural capabilities constrain agricultural transformation.

The Technology Acceptance Model (TAM) [5] and its extensions [6,7] explain technology adoption through perceived usefulness and perceived ease of use. The model has been applied to farmers' intention to adopt agriculture 5.0 technologies in Nepal [8] and, in its UTAUT form with risk perception, to micro-irrigation adoption in the water-scarce Bekaa Valley of Lebanon [9]. However, farmers' human capital has rarely been modelled explicitly as an antecedent of these perceptions, and evidence from Iraq is scarce.

This study addresses that gap by asking three questions: (1) How do digital literacy and extension support shape farmers' perceptions of smart agriculture technologies? (2) Through which paths do these human-capital factors affect intention and adoption? (3) How strongly do social influence and perceived cost and risk affect intention once human-capital factors are accounted for? The study contributes an extended TAM that integrates human-development variables, tests it with farm-level data from central and southern Iraq, and derives priorities for extension policy and rural capacity building.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

2.1. TAM and its agricultural applications

TAM explains technology use through two beliefs: perceived usefulness (PU), the degree to which a person believes that a technology will improve performance, and perceived ease of use (PEOU), the degree to which its use is free of effort [5]. Both shape behavioural intention (BI), which in turn drives actual use. TAM2 added social influence and cognitive antecedents of usefulness [6], and the Unified Theory of Acceptance and Use of Technology (UTAUT) added facilitating conditions [7]. In agriculture, Adrian et al. [10] found that perceived usefulness and confidence in using the technology predicted the intention to adopt precision agriculture in the United States, and Aubert et al. [11] found that ease of use and usefulness drove adoption in Canada. A review by Pierpaoli et al. [2] concluded that farmer education, skills and access to information are among the most consistent drivers of adoption.

2.2. Human-capital antecedents

Digital literacy (DL) is the farmer's ability to use smartphones, applications and digital interfaces and to interpret digital information. Farmers with higher digital literacy need less effort to learn a sensor dashboard or an irrigation application and better understand how data improve decision-making.

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H1. Digital literacy positively affects PEOU.

H2. Digital literacy positively affects PU.

Extension support (EXT) comprises the training, demonstrations and technical assistance provided by extension services, cooperatives, universities and suppliers. Extension builds skills, reduces uncertainty and provides the facilitating conditions that UTAUT identifies as a direct determinant of use [7].

H3. Extension support positively affects PEOU.

H4. Extension support positively affects PU.

H5. Extension support positively affects BI.

H6. Extension support positively affects adoption behaviour (AB).

2.3. Core TAM relations

H7. PEOU positively affects PU.

H8. PU positively affects BI.

H9. PEOU positively affects BI.

H10. BI positively affects AB.

2.4. Social and economic factors

In rural communities, decisions are influenced by the views of neighbours, relatives and lead farmers. Social influence (SI) refers to the perceived expectations of these referents. Perceived cost and risk (PCR) refers to concerns about purchase and maintenance costs, unreliable power supply and possible crop losses caused by technology failure.

H11. Social influence positively affects BI.

H12. Perceived cost and risk negatively affect BI.

The model also implies that digital literacy affects intention indirectly through PEOU and PU; these mediated effects are examined in Section 4.4. Fig. 1 shows the full research model with the estimated coefficients.

3. MATERIALS AND METHODS

3.1. Research design and population

A cross-sectional survey design was used. The population comprised farmers managing irrigated holdings in four provinces of the Middle Euphrates and central Iraq: Babylon, Karbala, Al-Qadisiyah and Wasit. These provinces combine large irrigated areas, acute water shortages and active extension programmes promoting modern irrigation.

3.2. Sampling and data collection

A multi-stage sampling design was applied. First, two agricultural districts were selected in each province in proportion to irrigated area. Second, villages were selected randomly from lists held by the agricultural directorates. Third, farmers were selected systematically from the registered farmer lists of each village. The minimum sample for a population of more than 100,000 at 95% confidence and 5% error is 384 [12]; this also

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exceeds the requirement of the inverse square-root method for detecting path coefficients of 0.15 at the 5% significance level in PLS-SEM [13]. Questionnaires were administered face-to-face in Arabic by trained enumerators from Al-Mussaib Technical College after informed consent had been obtained,. Of 420 questionnaires administered, 386 complete responses were retained (response rate 91.9%). The respondent profile is given in Table 1.

Table 1. Respondent profile (n = 386).

Characteristic	Category	Share (%)
Province	Babylon / Al-Qadisiyah / Wasit / Karbala	35.2 / 27.2 / 20.2 / 17.4
Gender	Male / Female	86.3 / 13.7
Education	None or primary	25.4
	Intermediate or secondary	39.4
	Diploma	15.0
	Bachelor or higher	20.2
Age	Mean 44.2 years (SD 10.7)	–
Farm size	Median 22 dunum (5.5 ha)	–

3.3. Measurement

All constructs were measured with multi-item reflective scales adapted from established sources and rated on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). PU, PEOU and BI items were adapted from Davis [5] and Venkatesh and Davis [6], and SI items from Venkatesh et al. [7]; DL, EXT, PCR and AB items were developed from Pierpaoli et al. [2] and Aubert et al. [11] and adapted to Iraqi conditions. The instrument was translated into Arabic and back-translated, reviewed by three experts in agricultural engineering and extension, and pilot-tested with 30 farmers who were excluded from the main sample. The full questionnaire is given in Appendix A.

3.4. Data analysis

PLS-SEM was used because the model is predictive and complex, includes several mediating paths, and Likert-scale data may depart from multivariate normality [13]. The analysis followed two stages. The measurement model was assessed through indicator loadings (≥ 0.70), internal consistency (Cronbach's α and composite reliability, CR ≥ 0.70), convergent validity (average variance extracted, AVE ≥ 0.50) and discriminant validity (Fornell–Larcker criterion [14] and heterotrait–monotrait ratio, HTMT < 0.85 [15]). The structural model was assessed through collinearity (VIF < 3), path coefficients with 2,000 bootstrap resamples, R^2, effect sizes f^2 and out-of-sample predictive relevance ($Q^2_{predict}$, 10-fold) [16]. Common method bias was examined with Harman's single-factor test and the full-collinearity VIF approach [17].

4. RESULTS

4.1. Common method bias

The first unrotated factor in Harman's test explained 26.7% of the variance, well below 50%, and all full-collinearity VIFs lay between 1.07 and 1.81, below the threshold of 3.3 [17]. Common method bias is therefore unlikely to distort the results.

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4.2. Measurement model

All indicator loadings exceeded 0.70 (range 0.736–0.913). Cronbach's α ranged from 0.785 to 0.870 and CR from 0.873 to 0.911, confirming internal consistency. AVE values ranged from 0.632 to 0.772, above the 0.50 threshold, confirming convergent validity (Table 2).

Table 2. Reliability and convergent validity of the constructs.

Construct	Items	Loading range	Cronbach's α	CR	AVE
Digital literacy (DL)	4	0.736–0.833	0.806	0.873	0.632
Extension support (EXT)	4	0.797–0.876	0.870	0.911	0.719
Social influence (SI)	3	0.844–0.913	0.852	0.910	0.772
Perceived cost and risk (PCR)	4	0.766–0.905	0.854	0.900	0.694
Perceived ease of use (PEOU)	4	0.793–0.860	0.846	0.897	0.685
Perceived usefulness (PU)	4	0.831–0.857	0.864	0.907	0.710
Behavioural intention (BI)	3	0.851–0.884	0.840	0.905	0.760
Adoption behaviour (AB)	3	0.808–0.881	0.785	0.873	0.696

CR: composite reliability; AVE: average variance extracted.

Discriminant validity was established by both criteria. The square root of each construct's AVE (diagonal of Table 3) exceeded its correlations with all other constructs, and all HTMT ratios were below 0.85, the highest being 0.61 (between BI and AB).

Table 3. Fornell–Larcker criterion (square root of AVE on the diagonal, in bold).

	DL	EXT	SI	PCR	PEOU	PU	BI	AB
DL	**0.795**							
EXT	0.344	**0.848**						
SI	0.138	0.252	**0.879**					
PCR	−0.119	−0.049	0.058	**0.833**				
PEOU	0.478	0.372	0.104	−0.095	**0.828**			
PU	0.403	0.398	0.152	−0.086	0.473	**0.843**		
BI	0.378	0.361	0.229	−0.223	0.417	0.485	**0.872**	
AB	0.140	0.270	0.203	−0.109	0.271	0.282	0.506	**0.834**

4.3. Structural model

Inner-model VIFs for the predictors of intention ranged from 1.02 to 1.40, so collinearity is not a concern. Fig. 1 shows the estimated model and Table 4 the hypothesis tests.

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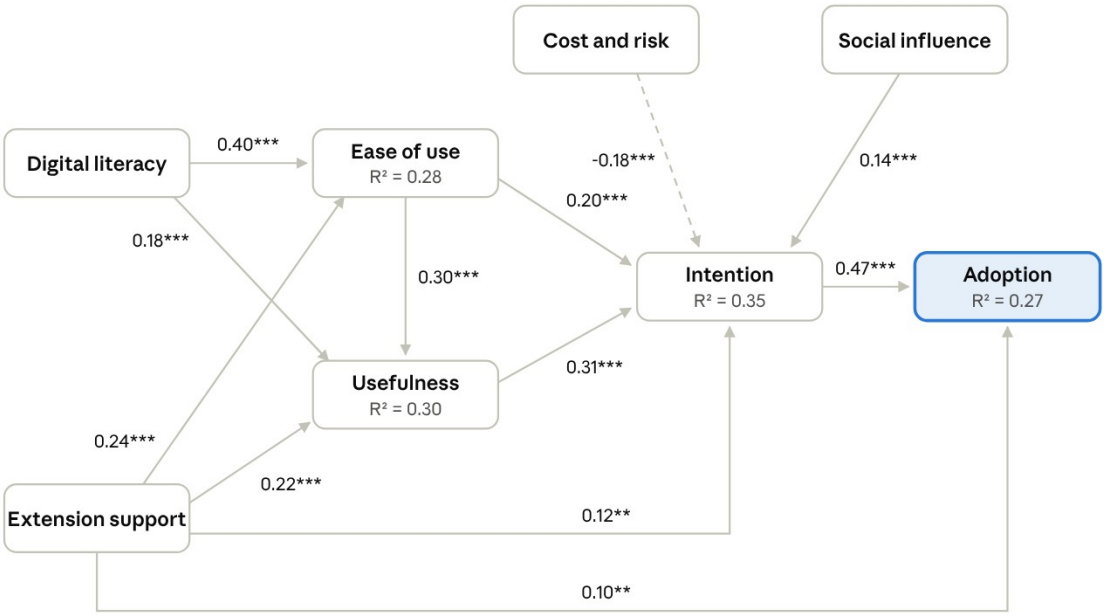


Fig. 1. Estimated research model: standardised PLS path coefficients and R^2 (n = 386). *** P < 0.01; ** P < 0.05 (2,000 bootstrap resamples); dashed arrow = negative effect.

Table 4. Results of hypothesis testing (2,000 bootstrap resamples).

Hypothesis	Path	β	t	P	95% CI	Decision
H1	DL → PEOU	0.396	9.63	< 0.001	[0.314, 0.478]	Supported
H2	DL → PU	0.181	3.84	< 0.001	[0.089, 0.275]	Supported
H3	EXT → PEOU	0.236	4.94	< 0.001	[0.148, 0.331]	Supported
H4	EXT → PU	0.222	4.96	< 0.001	[0.138, 0.313]	Supported
H5	EXT → BI	0.122	2.47	0.014	[0.021, 0.213]	Supported
H6	EXT → AB	0.101	2.18	0.029	[0.010, 0.191]	Supported
H7	PEOU → PU	0.304	6.52	< 0.001	[0.213, 0.395]	Supported
H8	PU → BI	0.307	6.62	< 0.001	[0.211, 0.399]	Supported
H9	PEOU → BI	0.195	4.07	< 0.001	[0.099, 0.288]	Supported
H10	BI → AB	0.469	11.53	< 0.001	[0.393, 0.548]	Supported
H11	SI → BI	0.142	3.22	0.001	[0.062, 0.229]	Supported
H12	PCR → BI	−0.180	−4.63	< 0.001	[−0.258, −0.105]	Supported

Table 5. Explanatory and predictive power of the model.

Endogenous construct	R^2	$Q^2_{predict}$
Perceived ease of use	0.277	0.261
Perceived usefulness	0.305	0.289
Behavioural intention	0.347	0.323
Adoption behaviour	0.265	0.248

All R^2 values are moderate for behavioural research, and all $Q^2_{predict}$ values are well above zero, indicating predictive relevance (Table 5). Intention had a medium-to-large effect on adoption (f^2 = 0.26). Usefulness had a small-to-medium effect on intention (f^2 = 0.10),

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whereas cost and risk (0.05), ease of use (0.04), social influence (0.03) and extension (0.02) had small effects. Extension also had a small direct effect on adoption ($f^2 = 0.01$).

4.4. Mediation and total effects

Table 6. Indirect and total effects (bootstrap 95% confidence intervals).

Effect	Estimate	t	95% CI
DL → PEOU → BI	0.077	3.52	[0.037, 0.123]
DL → PU → BI	0.056	3.09	[0.024, 0.095]
DL → PEOU → PU → BI	0.037	4.19	[0.022, 0.057]
Total effect DL → BI	0.170	6.62	[0.123, 0.221]
Total effect DL → AB	0.080	5.46	[0.054, 0.111]
Total effect EXT → BI	0.258	5.59	[0.163, 0.346]
Total effect EXT → AB	0.222	4.66	[0.123, 0.312]

Digital literacy has no direct path to intention in the model; its effect is fully transmitted through ease of use and usefulness, with the largest share running through ease of use (Table 6). Extension support acts through both direct and indirect paths and has the largest total effect on adoption of any exogenous construct.

5. DISCUSSION

The results confirm the core TAM relationships in Iraqi agriculture: farmers' intention is determined by perceived usefulness and ease of use, and intention in turn drives adoption. The main contribution of the study, however, is the identification of human-capital antecedents of these perceptions.

Digital literacy strongly shapes farmers' perceptions. It makes the largest single contribution to perceived ease of use, and its entire effect on intention is mediated by ease of use and usefulness. Farmers who use a smartphone comfortably perceive sensor dashboards and irrigation applications as easier to use and more useful. This is consistent with the view that a skills gap, and not only a cost gap, slows the diffusion of smart irrigation [2,3]. With 25% of respondents having at most primary education, this gap is considerable in the study area.

Extension support is the most versatile driver in the model. It affects ease of use and usefulness as well as intention and adoption directly, and it has the largest total effect on adoption. Its direct effect on adoption, after intention is controlled for, corresponds to the facilitating conditions of UTAUT [7], such as help with installation and troubleshooting. Iraqi extension services, however, are understaffed and oriented towards traditional crops and practices. Retooling extension for digital technologies therefore appears to be the most promising intervention for increasing adoption.

Cost, risk and social influence also matter, but to a lesser extent. Perceived cost and risk reduce intention, reflecting unstable electricity supply, maintenance requirements and the high price of imported equipment; a comparable deterrent effect of risk perception was reported for micro-irrigation adopters in Lebanon [9]. The smaller but significant effect of social influence suggests that demonstration farms and lead-farmer networks can accelerate diffusion.

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5.1. Practical implications

1. Digital literacy programmes for farmers: training in smartphone use, reading sensor data and using irrigation applications should be provided before, or together with, equipment grants.
2. Digitally capable extension services: extension agents should be trained in IoT-based irrigation, and each agricultural directorate needs technicians able to install and maintain the equipment; technical colleges such as Al-Mussaib Technical College can deliver this training.
3. Risk-sharing finance: equipment grants, pay-for-service models, leasing through the Agricultural Bank and solar-powered irrigation controllers that reduce dependence on the grid can substantially lower costs and risk.
4. Peer learning: demonstration plots on the farms of lead farmers in each district can speed up adoption.

5.2. Limitations

Because the study is cross-sectional, causal conclusions rest on theory rather than design. Self-reported adoption may be overestimated. The sample covers four provinces of central and southern Iraq, and results may differ in the Kurdistan Region or in the rain-fed areas of northern Iraq. Future studies should use longitudinal designs, objective adoption records from agricultural directorates and multi-group analyses comparing farmers by education, farm size and gender.

6. CONCLUSIONS

This study extended TAM with two human-capital constructs, digital literacy and extension support, to explain the adoption of smart agriculture and smart irrigation by farmers in central and southern Iraq. PLS-SEM analysis of 386 survey responses supported all twelve hypotheses. Digital literacy influences adoption through perceived ease of use and perceived usefulness, whereas extension support acts at every stage of the adoption process and has the largest total effect on adoption. Perceived cost and risk act as a barrier and social influence as a facilitator.

The principal conclusion is that modernising Iraqi irrigation is as much a human-development project as an engineering one. Water-saving technologies can be adopted widely only if farmers have the necessary skills and are supported by a capable extension service. Agricultural water policy and rural human-development policy should therefore be designed and financed together.

AUTHOR CONTRIBUTIONS

Fakhri Mahdi Hamad: Conceptualization, Methodology, Formal analysis, Writing – original draft. Abbas Mahdi Kadhim: Investigation, Data curation, Writing – review & editing. Salam Yaseen Taha: Investigation, Validation, Writing – review & editing. All authors have read and approved the final manuscript.

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DECLARATION OF COMPETING INTEREST

The authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

The anonymised survey data are available from the corresponding author upon reasonable request.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The survey protocol was reviewed and approved by the Ethics Committee of Al-Mussaib Technical College, Al-Furat Al-Awsat Technical University (Approval No. 101/ALMS, dated 10 November 2026). Participation was voluntary and anonymous, and informed consent was obtained from all participants before data collection.

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APPENDIX A. QUESTIONNAIRE ITEMS (FIVE-POINT LIKERT SCALE)

Table 7. Measurement items.

Code	Item
DL1	I can use a smartphone to search for agricultural information.
DL2	I can install and use mobile applications without help.
DL3	I can read and understand charts and numbers shown on a digital screen.
DL4	I use messaging apps or social media to exchange farming information.
EXT1	Extension staff have trained me on modern irrigation methods.
EXT2	I have attended a field demonstration of smart irrigation or sensors.
EXT3	I can obtain technical help when I have a problem with irrigation equipment.
EXT4	Extension services provide advice that is relevant to my farm.
SI1	Farmers whose opinion I respect think I should use smart irrigation.
SI2	Successful farmers in my area use or plan to use these technologies.
SI3	My family supports investing in new irrigation technology.
PCR1	The purchase cost of smart irrigation equipment is too high for me.
PCR2	I worry that equipment will fail because of power cuts.
PCR3	Maintenance and spare parts are hard to obtain.
PCR4	Using new technology could put my crop at risk.
PEOU1	Learning to use smart irrigation systems would be easy for me.
PEOU2	The instructions of these systems are clear and understandable.
PEOU3	It would be easy to become skilful at using these systems.
PEOU4	Operating sensors and controllers would not require much effort.
PU1	Smart irrigation would reduce the water I use.
PU2	Smart irrigation would increase my crop yield.
PU3	These technologies would reduce my labour and energy costs.
PU4	Overall, smart agriculture technologies would be useful on my farm.
BI1	I intend to use smart irrigation in the next two seasons.
BI2	I plan to recommend these technologies to other farmers.
BI3	I would invest in smart irrigation if support were available.
AB1	I currently use at least one smart agriculture technology (sensor, controller, app).
AB2	I schedule irrigation based on measured soil moisture or app advice.
AB3	I have increased my use of modern irrigation over the past two years.

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