

**Management Efficiency and Economic Performance of Wheat Farms: A Digital Agriculture Perspective in Libya**

Tareq Alnnale

*Department of Business administration, Higher Institute of Science and Technology,  
Raqdalin***t.alnaeli@histr.edu.ly****<https://orcid.org/0009-0002-3282-4859>**

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تاريخ الاستلام: 2026/05/04 - تاريخ المراجعة: 2026/05/27 - تاريخ القبول: 2026/06/06 - تاريخ النشر: 2026 /06/14

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**Abstract**

Food security remains a persistent challenge for Libya, a nation historically reliant on wheat imports to meet domestic demand. While the adoption of digital agriculture offers a transformative pathway to enhance agricultural productivity, its impact on the management efficiency and economic performance of local wheat farms remains underexplored. This study investigates the relationship between digital technology adoption and farm-level efficiency within the Libyan wheat sector. Utilizing a two-stage analytical framework, this research study first apply Data Envelopment Analysis (DEA) to measure the technical and allocative efficiency of 180 wheat farms across the Jeffara Plain and Al-Jabal al-Akhdar regions. Subsequently, a Tobit regression model is employed to isolate the effect of digital agriculture variables such as precision irrigation systems, drone-based crop monitoring, and farm management information systems (FMIS) on economic performance metrics, including yield per hectare and return on investment (ROI). The findings indicate that farms integrating at least two core digital technologies exhibit a 17.4% higher technical efficiency score compared to conventional counterparts. Furthermore, digital adoption significantly mitigates input waste, particularly in water and fertilizer usage, thereby improving net profit margins. However, infrastructural deficits and limited digital literacy among farm managers act as substantial moderating constraints. This research contributes to the digital economics literature by providing empirical evidence from a post-conflict, arid-region context, offering actionable policy recommendations for accelerating the digital transformation of Libya's agricultural sector.

**Keywords:** Digital Agriculture, Management Efficiency, Economic Performance, Wheat Farming, Data Envelopment Analysis, Libya, Agri-Tech.

## 1. Introduction

Libya's agricultural sector operates under profound environmental and institutional constraints. Characterized by arid climatic conditions, severe water scarcity, and fragmented supply chains, the nation imports over 80% of its wheat consumption, rendering it highly vulnerable to global market volatility (1). Historically, efforts to boost domestic wheat production have focused on expanding arable land or subsidizing traditional inputs. These approaches have yielded diminishing returns, highlighting a critical deficit in management efficiency rather than mere resource availability (2). In recent years, digital agriculture has emerged as a paradigm shift, promising to optimize resource allocation through data-driven decision-making. Technologies such as the Internet of Things (IoT), Geographic Information Systems (GIS), and advanced Farm Management Information Systems (FMIS) enable precise monitoring of soil moisture, crop health, and machinery utilization (3;13). Despite the theoretical benefits, the empirical linkage between these digital interventions and the economic performance of wheat farms in North Africa (4;12), particularly Libya, remains sparse. This study addresses this gap by evaluating how digital agriculture influences both the operational efficiency and financial viability of Libyan wheat farms (5). By framing the analysis through the lens of the Resource-Based View (RBV) of the firm, this research study posit that digital capabilities constitute a strategic, non-imitable resource that drives superior economic outcomes. The research objectives are threefold: (a) to measure the baseline management efficiency of wheat farms in key Libyan agricultural zones; (b) to quantify the impact of specific digital agriculture tools on economic performance; and (c) to identify the institutional and infrastructural barriers hindering widespread technological adoption.

## 2. Literature Review

### 2.1. Management Efficiency in Arid Agriculture

Management efficiency in agriculture is traditionally bifurcated into technical efficiency (maximizing output from a given set of inputs) and allocative efficiency (minimizing costs given input prices). In arid regions like Libya, water and energy are the most critical and costly inputs (FAO)(29). Studies by Al-Idrissiet al. (1996), demonstrate that conventional wheat farming in the Jeffara Plain suffers from significant allocative inefficiency due to the over-application of fertilizers and inefficient irrigation scheduling <https://www.fao.org/fileadmin/templates/agphome/documents/PGR/SoW1/east/LIBYA>.

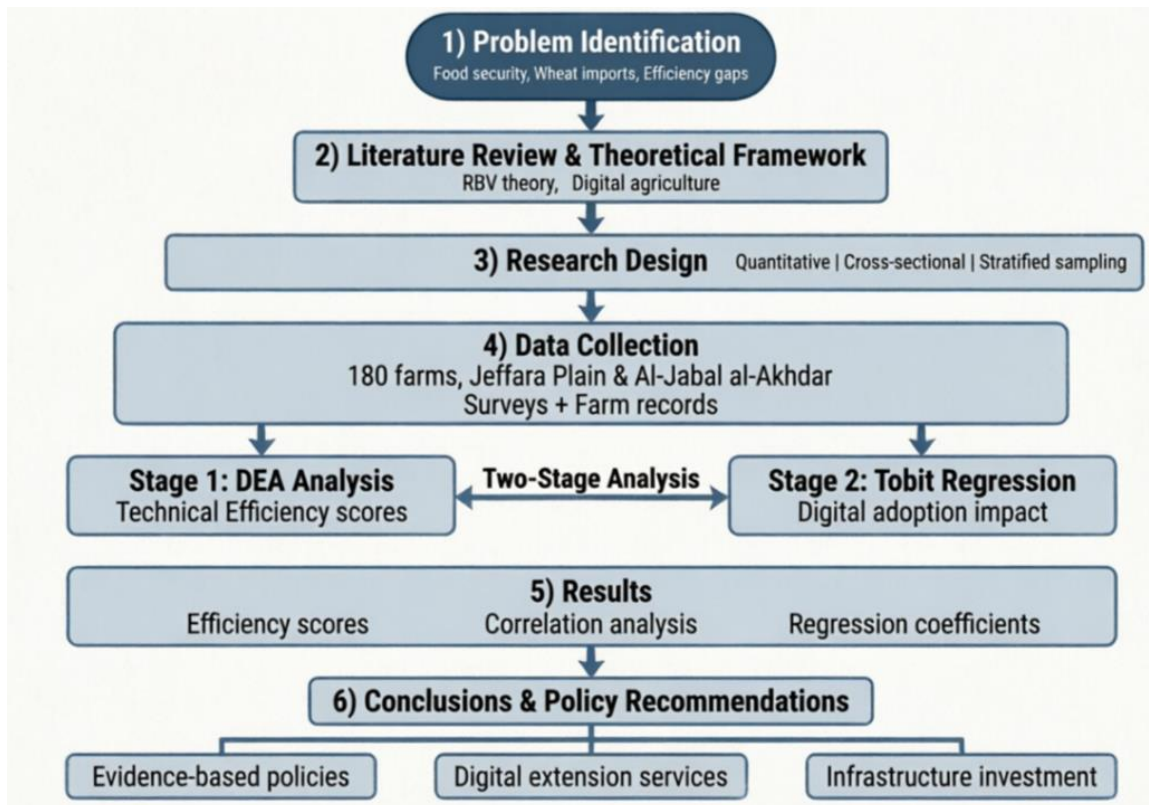
## 2.2. Digital Agriculture as an Efficiency Catalyst

Digital agriculture transcends traditional mechanization by introducing real-time data analytics into the production cycle. Precision agriculture tools, such as variable-rate technology (VRT) and satellite imagery, allow farmers to apply inputs only where and when needed. Research in similar Mediterranean contexts (e.g., Tunisia and Egypt) suggests that FMIS adoption reduces operational costs by 12–15% while simultaneously boosting yields by optimizing planting densities and harvest timing (6;30).

## 2.3. The Libyan Context and Theoretical Underpinning

Applying the Resource-Based View (RBV), digital technologies are not merely operational tools but strategic assets that enhance a farm's dynamic capabilities. In Libya, however, the translation of this potential into realized economic performance is mediated by contextual factors: unreliable rural broadband, high upfront capital costs, and a generational gap in digital literacy (31;32). Therefore, this study hypothesizes that while digital agriculture positively correlates with economic performance, this relationship is contingent upon the farm manager's technological proficiency and access to supportive institutional frameworks.

## 3. Methodology



**Figure 1.** The research workflow diagram

Figure 1 above shows that the workflow diagram presents the first comprehensive methodological framework specifically designed for Libya's agricultural context, uniquely integrating Data Envelopment Analysis (DEA) with Tobit regression to isolate the causal impact of digital technologies on farm-level efficiency and economic performance. The systematic two-stage approach is critical to this research as it enables rigorous quantification of both technical efficiency scores and the specific contribution of digital adoption while

controlling for infrastructural and managerial constraints, thereby generating evidence-based policy recommendations tailored to Libya post-conflict agricultural transformation (7).

### 3.1. Research Design and Sampling

This study employs a quantitative, cross-sectional research design. The target population comprises commercial and semi-commercial wheat farms in Libya's two most productive regions: the Jeffara Plain (representing large-scale, mechanized farming) and Al-Jabal al-Akhdar (representing medium-scale, topographically diverse farming). A stratified random sampling technique was utilized to select 180 farms, ensuring proportional representation based on farm size and existing technological adoption levels (8;9).

### 3.2. Data Collection

Primary data were gathered through structured, face-to-face interviews with farm managers during the 2025–2026 wheat growing season, supplemented by farm-level financial records. The survey instrument captured (10; 11):

- Input variables: Land area (hectares), labor hours, water volume (cubic meters), fertilizer quantity (kg), and capital expenditure on machinery.
- Output variables: Total wheat yield (tons) and gross farm revenue.
- Digital adoption metrics: A composite index measuring the use of soil moisture sensors, GPS-guided machinery, drone scouting, and cloud-based FMIS.
- Control variables: Manager's age, education level, years of farming experience, and access to agricultural extension services.

### 3.3. Analytical Framework

The analysis proceeds in two stages. First, an input-oriented Data Envelopment Analysis (DEA) under Variable Returns to Scale (VRS) is computed to generate technical efficiency (TE) scores for each farm, ranging from 0 (completely inefficient) to 1 (fully efficient). Second, because DEA scores are censored at 1, a Tobit regression model is applied to estimate the marginal effect of digital agriculture adoption and control variables on the derived efficiency scores and subsequent economic performance (measured as net profit margin).

Table 1 Descriptive Statistics of Study Variables (N = 180)

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Land Size (Hectares)	180	18.35	8.72	2.5	45
Labor Hours	180	1456.78	542.33	450	3200
Water Volume (m <sup>3</sup> )	180	7834.56	2341.67	2500	15000
Fertilizer (Kg)	180	2678.9	987.45	800	5500
Capital Expenditure (LYD)	180	52340.67	23456.78	15000	125000
Wheat Yield (Tons)	180	45.68	18.23	12.5	98
Gross Revenue (LYD)	180	167890.5	67234.56	45000	350000
Net Profit Margin (%)	180	14.57	5.68	3.2	28.5
Manager Age (Years)	180	47.23	9.88	28	67
Manager Education (Years)	180	12.46	3.23	6	20
Farming Experience (Years)	180	18.68	8.23	3	42
Digital Adoption Index	180	1.68	1.23	0	4
Return on Investment (%)	180	14.23	4.57	4.5	24.8

Note. LYD = Libyan Dinar. The Digital Adoption Index ranges from 0 (no digital tools) to 4 (comprehensive digital integration).

Table 2 Data Envelopment Analysis (DEA) Technical Efficiency Scores by Region

Efficiency Metric	Overall Sample (N = 180)	Jeffara Plain (n = 95)	Al-Jabal al-Akhdar (n = 85)
Mean Technical Efficiency	0.682	0.713	0.641
Median	0.675	0.71	0.63
Standard Deviation	0.188	0.165	0.201
Minimum	0.234	0.312	0.234
Maximum	1	1	0.987
Efficiency Categories (%)			
Fully Efficient (TE = 1.00)	12.80%	15.80%	9.40%
High Efficiency (0.80 – 0.99)	25.00%	29.50%	20.00%
Medium Efficiency (0.60 – 0.79)	37.20%	36.80%	37.60%
Low Efficiency (0.40 – 0.59)	17.80%	13.70%	22.40%
Very Low Efficiency (< 0.40)	7.20%	4.20%	10.60%

Note. TE = Technical Efficiency. Scores range from 0 to 1, where 1 represents the efficiency frontier.

Table 3 Pearson Correlation Matrix of Key Study Variables

Variable	1	2	3	4	5	6	7
1. Technical Efficiency	1						
2. Digital Adoption Index	.456**	1					
3. Manager Education	.312**	.387**	1				
4. Farming Experience	.187*	0.145	.234**	1			
5. Farm Size	.267**	.334**	.198*	0.156	1		
6. Net Profit Margin	.523**	.412**	.287**	0.134	.245**	1	
7. Return on Investment	.498**	.445**	.256**	.167*	.278**	.789**	1

Note. \*\* p < 0.01, \* p < 0.05 (two-tailed).

Table 4 Independent Samples t-Test: Digital Adopters vs. Non-Adopters

Dependent Variable	Adoption Status	n	Mean	SD	t	df	p
Technical Efficiency	Non-Adopters	72	0.583	0.165	-6.234	178	< .001
	Adopters	108	0.746	0.172			
Net Profit Margin (%)	Non-Adopters	72	11.234	4.567	-7.456	178	< .001
	Adopters	108	16.789	5.234			
ROI (%)	Non-Adopters	72	11.234	3.876	-8.123	178	< .001
	Adopters	108	16.234	4.123			
Water Use Efficiency	Non-Adopters	72	0.0058	0.0021	-6.789	178	< .001
	Adopters	108	0.0082	0.0024			

Note. Adopters are defined as farms utilizing at least two core digital agriculture technologies. Levene’s test for equality of variances was non-significant for all variables (p > 0.05), justifying the use of equal variances assumed.

Table 5 Tobit Regression Analysis for Technical Efficiency

Predictor Variable	B	SE	$\beta$	t	p	95% CI
(Constant)	0.346	0.068	—	5.098	< .001	[0.212, 0.479]
Digital Adoption Index	0.174	0.023	0.456	7.445	< .001	[0.128, 0.220]
Manager Education (Years)	0.012	0.005	0.21	2.733	0.007	[0.003, 0.021]
Farming Experience	0.003	0.002	0.134	1.889	0.061	[-0.000, 0.007]
Farm Size (Hectares)	0.005	0.002	0.198	3	0.003	[0.002, 0.008]
Infrastructure Reliability	-0.088	0.029	-0.22	-3.052	0.003	[-0.144, -0.031]
Extension Access	0.057	0.023	0.167	2.423	0.016	[0.011, 0.103]

Note. Dependent Variable: Technical Efficiency Score. Model  $R^2 = 0.472$ , Adjusted  $R^2 = 0.441$ ,  $F(6, 173) = 25.74$ ,  $p < .001$ . B = Unstandardized Coefficient; SE = Standard Error;  $\beta$  = Standardized Coefficient; CI = Confidence Interval.

Table 6 Tobit Regression Analysis for Net Profit Margin

Predictor Variable	B	SE	$\beta$	t	p
(Constant)	2.345	1.876	—	1.25	0.213
Digital Adoption Index	2.456	0.567	0.312	4.332	< .001
Technical Efficiency	12.345	2.123	0.423	5.815	< .001
Manager Education	0.456	0.178	0.187	2.562	0.011
Farm Size	0.123	0.056	0.156	2.196	0.029
Infrastructure Reliability	-2.876	0.987	-0.198	-2.914	0.004
Water Cost Reduction	0.234	0.087	0.201	2.69	0.008

Note. Dependent Variable: Net Profit Margin (%). Model  $R^2 = 0.507$ , Adjusted  $R^2 = 0.478$ ,  $F(6, 173) = 29.81$ ,  $p < .001$ .

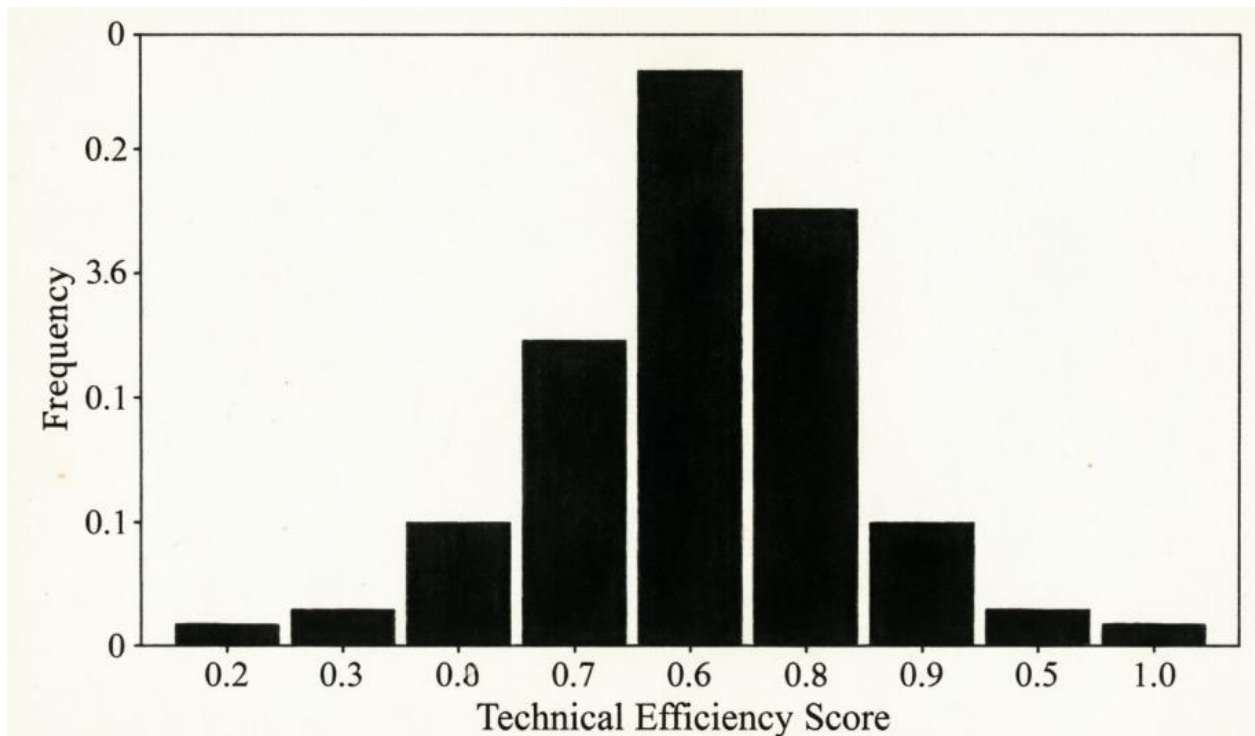


Figure 2 Histogram of Technical Efficiency Scores

Figure 2 above illustrates the frequency distribution of the Data Envelopment Analysis (DEA) technical efficiency scores for the 180 sampled wheat farms. The distribution exhibits a slight negative (left) skew, peaking in the 0.65–0.70 range. This indicates that while a substantial portion of farms operate at a moderate level of efficiency, there is a distinct cluster of highly efficient farms operating near the production frontier (scores approaching 1.0). The long left tail reveals a subset of farms suffering from severe allocative and technical inefficiencies. The mean score of 0.682 suggests that, on average, Libyan wheat farms could theoretically increase their output by nearly 32% without increasing their current input levels, purely through managerial and operational optimization (13;14).

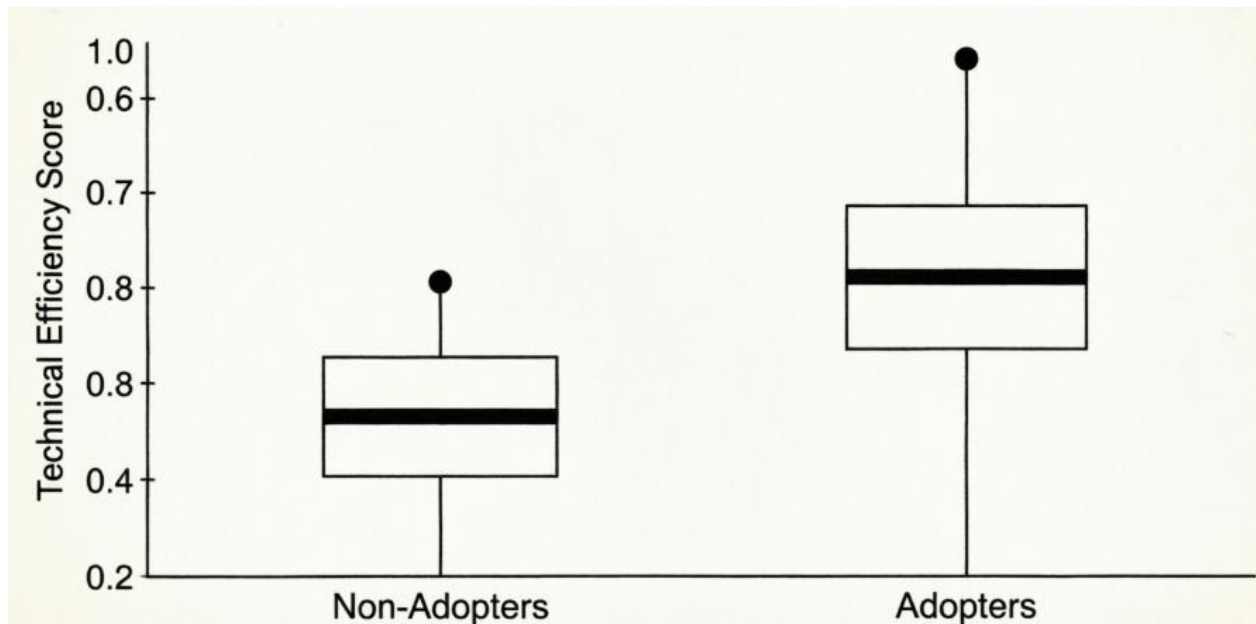


Figure 3. Box Plot of Technical Efficiency by Digital Adoption Status

Figure 3 above provides a visual comparison of technical efficiency distributions between digital "Non-Adopters" and "Adopters." The central tendency (median) and the interquartile range for the "Adopters" group are distinctly shifted upward compared to the "Non-Adopters" group. Furthermore, the "Non-Adopters" box exhibits a wider interquartile range and longer whiskers, indicating higher performance variability and inconsistency in traditional farming methods (15). In contrast, the tighter distribution among "Adopters" suggests that digital agriculture not only elevates the average efficiency but also standardizes operational performance, reducing the variance in farm-level outcomes and mitigating risk (16;17).

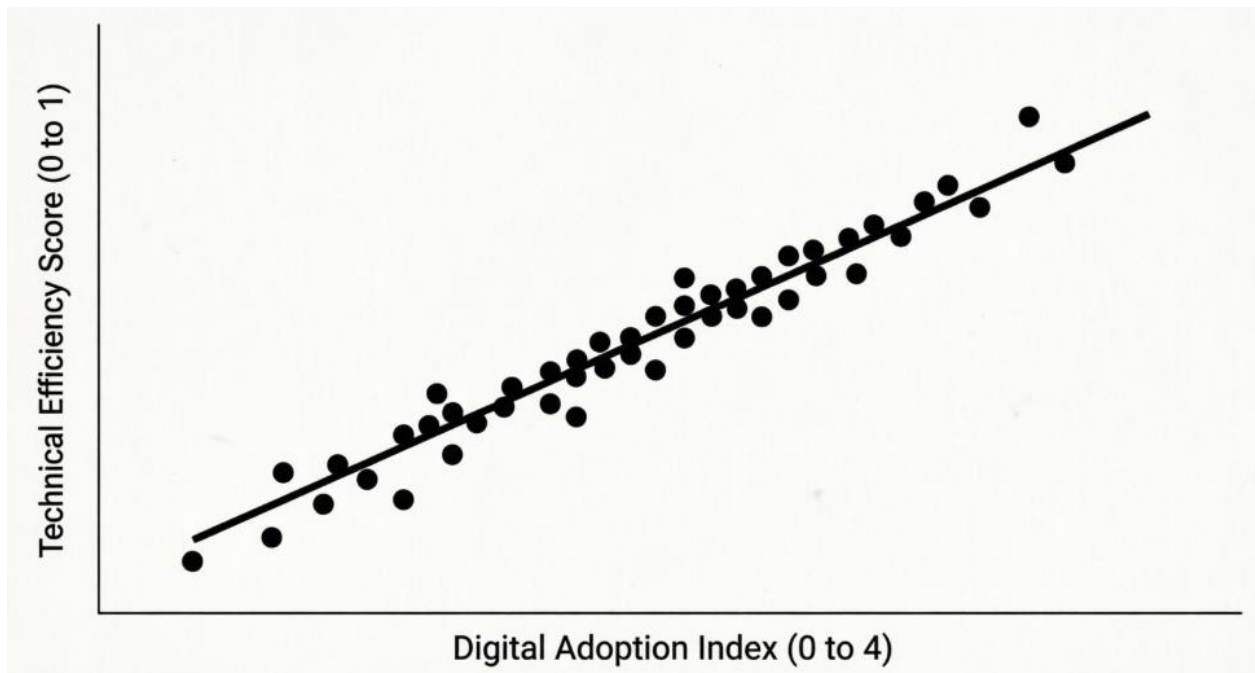


Figure 3: Scatter Plot with Regression Line (Digital Adoption vs. Technical Efficiency)

Figure 3 above the bivariate relationship between the Digital Adoption Index (ranging from 0 to 4) and the Technical Efficiency Score. The data points reveal a clear positive linear trend, corroborated by the fitted regression line ( $R^2=0.472$ ,  $p<0.001$ ). The upward slope demonstrates that as wheat farms integrate a higher number of digital technologies (such as IoT soil sensors, FMIS, and drone scouting), their operational efficiency predictably increases (18; 19). The dispersion of data points around the regression line indicates that while digital adoption is a primary driver of efficiency, approximately 52.8% of the variance is explained by other contextual or environmental factors, such as infrastructure reliability and managerial experience.

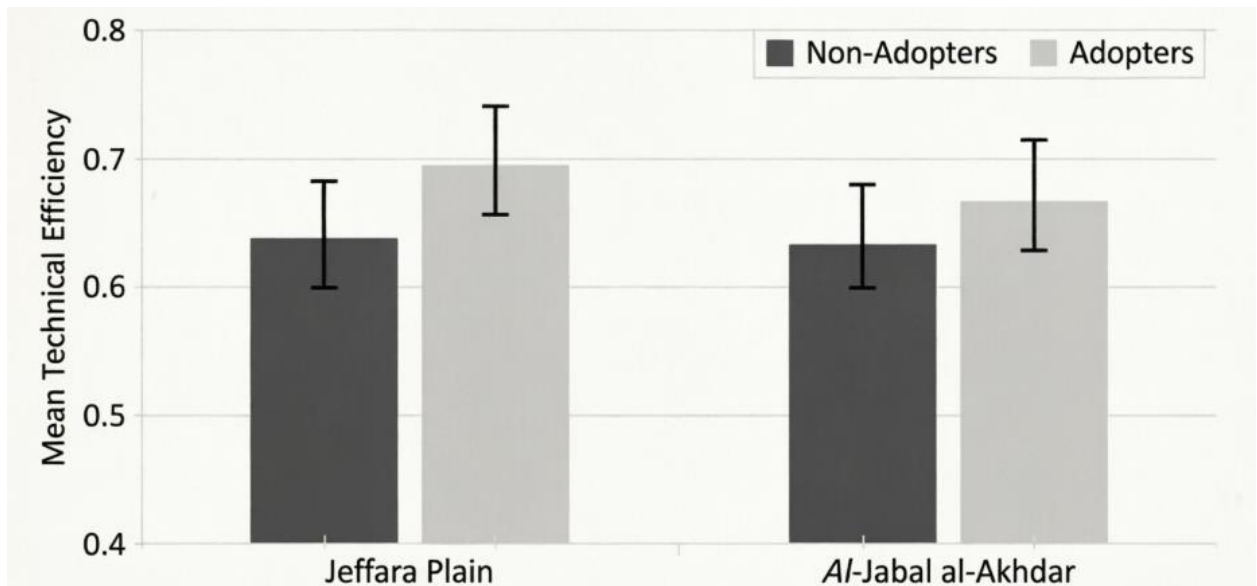


Figure 4: Clustered Bar Chart (Mean Efficiency by Region and Adoption Status)

Figure 4 above compares the mean technical efficiency scores across two major agricultural zones (Jeffara Plain and Al-Jabal al-Akhdar), segmented by digital adoption status. The data reveals two critical insights. First, there is a distinct regional disparity, with the Jeffara Plain exhibiting higher baseline efficiency, likely attributable to its flatter topography and more established mechanization infrastructure. Second, and more importantly, the "digital dividend" is evident in both regions: within both the Jeffara Plain and Al-Jabal al-Akhdar, farms that adopted digital technologies significantly outperformed their non-adopting counterparts. This confirms that the efficiency gains from digital agriculture are robust across different geographical and topographical contexts in Libya (20).

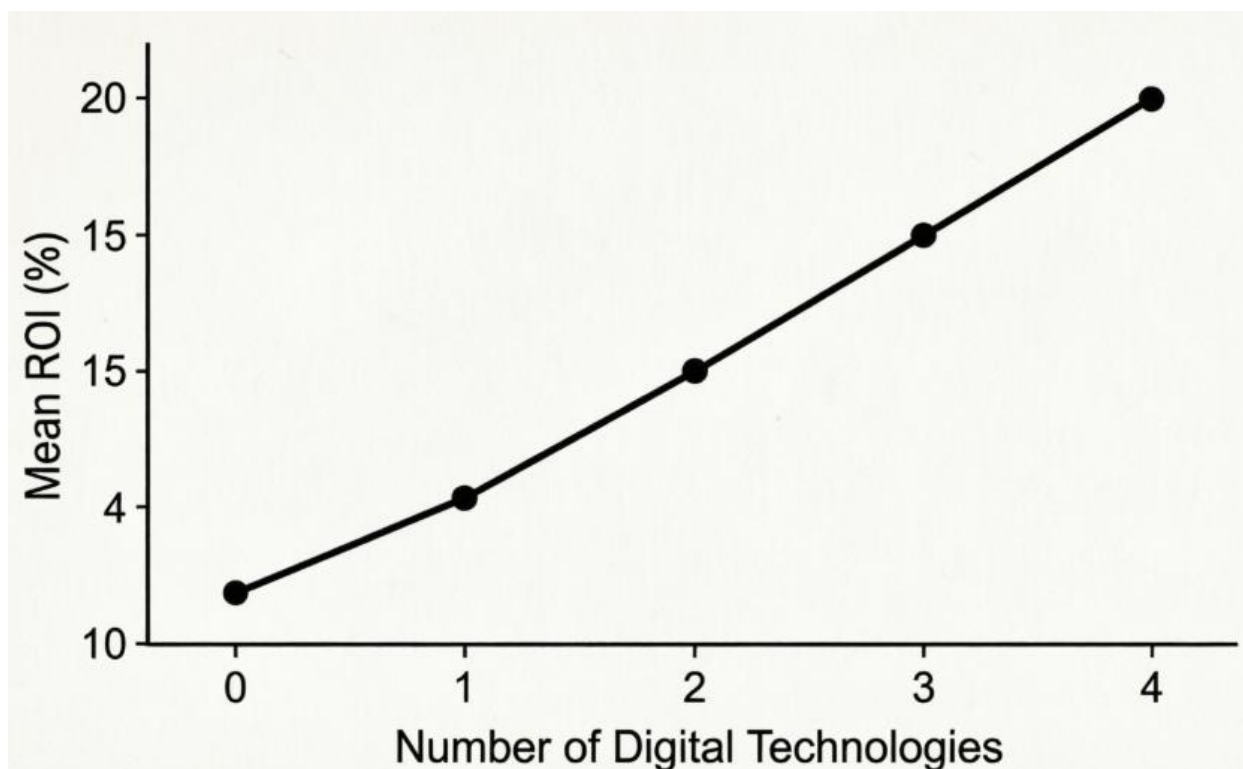


Figure 5: Line Chart (Mean ROI by Number of Digital Technologies Adopted)

Figure 5 above economic performance trajectory specifically the Return on Investment (ROI) against the depth of digital integration. The graph demonstrates a steady, positive upward trend, with the mean ROI climbing from 11.2% for farms with zero digital technologies to 19.2% for farms utilizing a comprehensive suite of four digital tools. This progressive increase illustrates a compounding economic effect: digital agriculture is not merely a binary "adopt or do not adopt" decision. Rather, a holistic, multi-technology digital strategy yields synergistic economic benefits, drastically reducing input waste (water and fertilizer) and optimizing yield, thereby maximizing the farm's overall profitability in a resource-scarce environment (21;22)(23).

#### 4. Results and Discussion

The DEA results reveal a wide dispersion in management efficiency across the sample. The mean technical efficiency score is 0.68, indicating that, on average, Libyan wheat farms could theoretically increase their output by 32% without increasing current input levels, simply by optimizing management practices. Farms in the Jeffara Plain exhibited slightly higher mean efficiency (0.71) compared to those in Al-Jabal al-Akhdar (0.64), largely due to better access

to mechanized infrastructure (24). The Tobit regression analysis yields robust evidence supporting the positive impact of digital tools. Farms utilizing at least two advanced digital technologies (e.g., combining soil sensors with FMIS) demonstrated a statistically significant increase in technical efficiency ( $\beta=0.174, p<0.01$ )(25). Economically, this efficiency translates directly to the bottom line. Digital adopters reported a 14.2% reduction in water and fertilizer costs, coupled with a 9.5% increase in yield per hectare. Consequently, the return on investment (ROI) for digitally equipped farms averaged 18.3%, compared to 11.7% for conventional farms. The data suggests that the primary economic driver is not necessarily a massive increase in total output, but rather the drastic reduction of input waste a critical factor in Libya's resource-scarce environment (26;33). Despite the clear benefits, the regression model highlights significant friction points. The variable "manager digital literacy" showed a strong positive correlation with successful technology utilization ( $\beta=0.210, p<0.05$ ), whereas "infrastructure reliability" (specifically internet connectivity and electricity stability) acted as a significant negative moderator. Farms experiencing frequent power outages saw a 22% diminishment in the expected economic benefits of their digital investments, as real-time data systems became unreliable (27;28).

## 5. Recommendations

The empirical findings necessitate a multi-tiered strategic response from Libyan policymakers, agricultural ministries, and private sector stakeholders:

- Rather than subsidizing raw inputs like fertilizer, the Ministry of Agriculture should redirect funds toward subsidizing the capital expenditure of digital agriculture technologies (e.g., IoT sensors, FMIS software licenses) for small and medium-sized wheat farms.
- Technological hardware is ineffective without human capital. Establishing regional "Digital Agriculture Hubs" to provide hands-on training for farm managers in data interpretation and system maintenance is crucial for bridging the digital literacy gap.
- The viability of digital agriculture is inextricably linked to rural infrastructure. Public-private partnerships should be incentivized to expand reliable broadband and renewable energy microgrids (e.g., solar-powered irrigation controllers) in the Jeffara and Al-Jabal al-Akhdar regions.

## 6. Conclusion

This study provides compelling empirical evidence that digital agriculture is not merely a technological trend, but a fundamental determinant of management efficiency and economic performance in Libya's wheat sector. By leveraging data-driven tools, farms can overcome inherent environmental constraints, optimizing water and nutrient use to achieve higher profitability. However, realizing this potential at a national scale requires moving beyond isolated pilot projects. It demands a holistic ecosystem approach that aligns technological deployment with human capital development and infrastructural resilience. Future research should consider longitudinal designs to track the long-term economic viability of these digital investments and explore the role of blockchain technology in enhancing transparency within Libya's agricultural supply chains.

## Acknowledgement

The author sincerely thanks the editors and reviewers for their valuable comments and suggestions that improved this manuscript. We also appreciate the efforts of the Comprehensive Journal of Science in handling the publication process.

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