Exploring the Potential of AI-Driven Safety Management in Tunisia's Agriculture Sector: Trust, Readiness, and Barriers to Adoption

Abstract:

The agricultural sector in Tunisia is vital to the national economy, yet it remains a high-risk industry in terms of occupational health and safety (OHS). Workers in this sector face hazards ranging from exposure to pesticides, machinery accidents, and extreme weather conditions. Despite the rise of Artificial Intelligence (AI) in industrial safety management globally, AI's application in agricultural OHS is still in its infancy in Tunisia. This study explores the trust, readiness, and barriers to the adoption of AI-driven safety solutions in Tunisia's agricultural sector. Through a survey-based approach, data were collected from workers and managers in the agriculture industry, assessing their perceptions of AI reliability, willingness to integrate AI technologies, and organizational preparedness for adopting AI solutions. The findings reveal critical gaps in AI literacy, cultural factors, and technological infrastructure, with trust in AI being a significant determinant of its adoption. The research offers actionable insights into overcoming barriers to AI integration, potentially transforming safety management practices in Tunisia's agriculture sector and providing a roadmap for similar contexts in developing economies.

Keywords:
Artificial Intelligence (AI), Agricultural Safety Systems, Technology Acceptance Model (TAM), Technology Readiness Index (TRI), AI Trust and Ethics, Occupational Safety in Agriculture, Human–Technology Interaction, Barriers to AI Adoption, Digital Agriculture in Tunisia, Socio-Technical Systems, Occupational Health and Safety (OHS)

1. Introduction

1.1 Background

The agriculture sector in Tunisia remains a cornerstone of the economy, employing approximately 30% of the country's workforce and contributing to over 10% of its GDP (World Bank, 2023). Despite its economic importance, the sector remains highly vulnerable to various occupational health and safety (OHS) risks, which include machinery-related injuries, chemical exposure, and the adverse effects of extreme weather conditions (FAO, 2024). Agricultural workers are particularly exposed to physical hazards due to the reliance on machinery such as tractors and combines, as well as chemical hazards from the use of pesticides and fertilizers. Additionally, the lack of structured safety regulations and insufficient implementation of existing policies contribute to the high rates of workplace accidents (OECD, 2023).

In recent years, the integration of Artificial Intelligence (AI) technologies in various industries has shown promise in enhancing workplace safety by offering predictive analytics, real-time monitoring, and automated hazard detection systems (Santos et al., 2023). However, while sectors such as manufacturing and construction have seen considerable advancements in AI adoption for occupational safety, the agricultural sector, particularly in developing economies like Tunisia, remains underexplored in this regard. Tunisia's agricultural sector still heavily relies on manual inspections and reactive safety measures, which are often inadequate in mitigating emerging risks.

AI has the potential to transform agricultural OHS by identifying potential hazards before they occur, enhancing real-time monitoring of workers' health, and automating the detection of safety breaches through smart sensors, wearable technologies, and drones (Huang et al., 2023). Despite this potential, the integration of AI into the agriculture sector in Tunisia remains limited. There is a pressing need to explore the factors influencing the adoption of AI in agricultural safety management, particularly in terms of AI literacy, trust in AI systems, and organizational readiness.

1.2 Problem Statement

The challenge of adopting AI in occupational health and safety (OHS) within Tunisia's agricultural sector is compounded by several factors, including technological readiness, worker resistance, and the lack of trust in AI systems. While AI solutions have been successfully implemented in sectors such as manufacturing and construction, the agricultural sector's unique challenges—such as informal labour, limited technological infrastructure, and cultural resistance to change—create substantial barriers to AI adoption (Khan et al., 2024). Moreover, there is a lack of empirical research examining the perceived trust in AI systems and the organizational barriers to their integration in agricultural OHS.

Existing literature in Tunisia largely overlooks the role of AI in improving safety practices in agriculture, especially in terms of workers' perceptions of AI's reliability, its effectiveness in detecting risks, and its ability to foster a safer working environment. The current state of AI adoption in Tunisian agriculture remains ad hoc and lacks systematic investigation, especially regarding how AI-driven systems can address specific OHS challenges such as pesticide exposure and machinery-related accidents.

1.3 Research Objectives and Significance

This study aims to fill these gaps by examining the trust, readiness, and barriers to AI adoption in Tunisia's agricultural sector. Specifically, the research will:

1. Assess the awareness and understanding of AI technologies among agricultural workers and managers in Tunisia.
2. Evaluate the perceived trust in AI systems and their effectiveness in improving workplace safety.
3. Examine the organizational readiness to adopt AI technologies in agricultural OHS practices.
4. Identify the barriers to AI adoption in Tunisia's agriculture sector and propose actionable strategies to overcome them.

The significance of this research lies in its potential to transform agricultural safety management by exploring how AI technologies can be adapted and implemented in developing economies like Tunisia. Given the limited research on AI in agriculture-related OHS in Tunisia, this study will contribute valuable insights into the challenges and opportunities for AI-driven safety in agricultural workplaces. Additionally, it will provide policymakers, industry stakeholders, and researchers with evidence-based recommendations for promoting the adoption of AI technologies to reduce workplace accidents and improve the overall health of agricultural workers.

By focusing on Tunisia, a developing country with a significant agricultural workforce, this study will also provide contextual insights that could be applied to other similar economies facing comparable technological and socioeconomic barriers to AI adoption. Furthermore, the findings of this study will be essential for global research on AI in OHS in developing countries and can potentially serve as a model for integrating AI into agriculture in regions with limited technological infrastructure.

2. Literature Review

2.1 Occupational Health and Safety in Tunisia's Agriculture Sector

The agricultural sector in Tunisia is crucial to the economy, providing significant employment opportunities, especially in rural areas. However, it remains one of the most hazardous industries, with workers exposed to a range of physical and chemical hazards. These include machinery-related accidents, exposure to pesticides, and the adverse effects of extreme weather conditions (Chakroun et al., 2023). Pesticide exposure, in particular, remains a leading cause of illness among agricultural workers, contributing to both acute poisoning and chronic health issues such as cancer and respiratory problems (Benzarti et al., 2024).

The lack of safety culture and inadequate enforcement of existing regulations have been identified as key contributors to the high rate of accidents in this sector (Ben Sassi et al., 2023). In Tunisia, the National Institute for Occupational Safety and Health (INSS) has implemented regulations designed to reduce workplace risks in agriculture, but enforcement remains inconsistent, particularly in the more informal sectors (Zribi et al., 2023). Traditional safety management practices have focused on reactive measures such as accident reports and minimal compliance checks, leaving significant gaps in preventative safety management.

The introduction of AI technologies into agriculture, especially regarding occupational safety, is still in its infancy. Researchers have pointed out that although AI has shown great promise in sectors like manufacturing and construction, the specific needs of agricultural OHS require tailored AI solutions (Santos et al., 2023). There remains a significant lack of empirical studies that examine AI's potential for preventing agricultural accidents and enhancing the well-being of workers in Tunisia. Most studies that have explored AI's role in agricultural safety are limited to broader contexts and fail to address the unique challenges faced by Tunisian agricultural workers, such as informal labour and limited technological infrastructure (Khan et al., 2024).

2.2 Artificial Intelligence in Occupational Safety Management

AI's application in occupational health and safety (OHS) has revolutionized industries such as construction, manufacturing, and mining, where predictive models and automated hazard detection have successfully reduced the frequency and severity of workplace accidents (Gonzalez et al., 2024). In these industries, AI systems integrate data from wearables, drones, and sensors to monitor workers' health in real time, provide predictive analytics on accident likelihood, and automate compliance with safety standards (Huang et al., 2023). AI technologies can detect subtle patterns in large datasets that are difficult for human supervisors to identify, thereby enabling proactive interventions before accidents occur.

The potential benefits of AI in occupational safety management are well-documented in global studies. For example, AI systems equipped with machine learning algorithms can predict when a worker is likely to be exposed to high-risk conditions, such as pesticide exposure or extreme weather events, and trigger preventive measures (Lee et al., 2023). In high-risk industries like construction, AI has been credited with improving safety outcomes by monitoring workers' movements and environmental conditions to prevent falls, electrical accidents, and machinery malfunctions (Santos et al., 2023).

However, the adoption of AI in agricultural OHS faces specific challenges. Agricultural tasks are inherently variable, influenced by seasonal cycles, weather patterns, and manual labour intensity, which can make it difficult for AI systems to provide reliable predictions (Gonzalez et al., 2024). Moreover, most agricultural workers, particularly in Tunisia, lack access to advanced technologies and may have limited AI literacy. These barriers suggest that AI adoption must be contextualized to suit the specific needs and limitations of agricultural workers.

2.3 Trust in AI Systems

One of the critical determinants of AI adoption in any industry is the trust that workers, managers, and organizations place in AI systems (Agyemang et al., 2023). In the context of OHS, where worker safety is paramount, trust in AI becomes even more crucial. Workers must be assured that the AI systems they interact with are reliable, accurate, and transparent. Trust can be categorized into two main components: trust in the system's capability to perform tasks and trust in the organizational context that implements the system (Lee et al., 2023).

Studies have shown that perceived trust in AI is directly related to the system's accuracy, reliability, and openness about how decisions are made (Santos et al., 2024). Workers are more likely to adopt AI-based safety systems if they believe these systems will help prevent accidents and enhance their safety. For example, AI-powered wearables that monitor heart rate, body temperature, and pesticide exposure levels have been shown to increase worker confidence in AI technologies, especially when workers can verify the accuracy of the data being monitored (Gonzalez et al., 2023).

In Tunisia, where trust in technology may be relatively low due to limited exposure to advanced safety technologies, building trust in AI systems is a significant challenge. This challenge is compounded by concerns about data privacy, system malfunctions, and a lack of understanding about how AI algorithms work (Lee et al., 2024). Moreover, the absence of governmental regulations that ensure AI accountability and transparency in agriculture further exacerbates this issue.

2.4 Technology Readiness for AI Adoption

Technology readiness is another crucial factor influencing the adoption of AI in agriculture. Parasuraman and Colby (2015) define technology readiness as the individual and organizational willingness to embrace new technologies. AI readiness in agriculture involves several dimensions: organizational infrastructure, employee willingness, and the perceived value of AI in improving safety practices (Khan et al., 2024). In Tunisia, the agricultural sector faces substantial infrastructure challenges, including limited access to high-speed internet, a lack of advanced training in AI technologies, and low levels of digital literacy among workers.

Recent studies have shown that AI adoption in agriculture is heavily influenced by the availability of digital infrastructure and skilled labour (Santos et al., 2023). Countries with limited technological readiness face challenges in adopting advanced safety solutions, including AI-based systems. However, even in environments with low readiness, there are signs of increased interest in AI for safety, provided that training programs, awareness campaigns, and government incentives are implemented to improve AI literacy and technical capabilities (Zribi et al., 2023).

In Tunisia, agricultural workers' technology readiness is influenced by cultural attitudes toward innovation and organizational support for technology integration. Previous studies have highlighted the lack of trust in new technologies and cultural resistance to AI-driven change as significant barriers to adoption (Huang et al., 2023; Zribi et al., 2023). Therefore, a concerted effort is needed to improve digital literacy, foster a positive attitude toward AI technologies, and build the infrastructure necessary for successful AI adoption in agricultural OHS.

In addition to internal readiness factors, external institutional forces play a pivotal role in shaping technology adoption. Organizational support, such as leadership commitment, funding availability, and structured AI training programs, can significantly enhance the readiness of agricultural entities to integrate AI-driven safety systems. Moreover, regulatory policies that establish clear guidelines for AI deployment, data privacy, and ethical accountability can foster an environment of trust and standardization. In Tunisia, the absence of strong governmental incentives or regulatory enforcement related to AI in agriculture may limit both investment and experimentation. As a result, aligning AI adoption strategies with institutional frameworks and advocating for supportive policy reform are crucial steps in bridging the readiness gap.

3. Methodology

3.1 Research Design

This study employs a quantitative, cross-sectional research design to explore the role of trust and technology readiness in the behavioral intention to adopt AI-driven occupational health and safety (OHS) systems within Tunisia's agricultural sector—a context previously underexplored in safety technology literature. A deductive approach was utilized to empirically test a conceptual framework based on established behavioral technology acceptance models.

To analyse the complex interplay of latent variables and to validate the hypothesized relationships among constructs, the study applied Covariance-Based Structural Equation Modelling (CB-SEM) using AMOS 26.0. CB-SEM was selected over Partial Least Squares SEM (PLS-SEM) due to its superior capability in confirming theoretically grounded models and evaluating measurement errors and model fit with high precision (Hair et al., 2021).

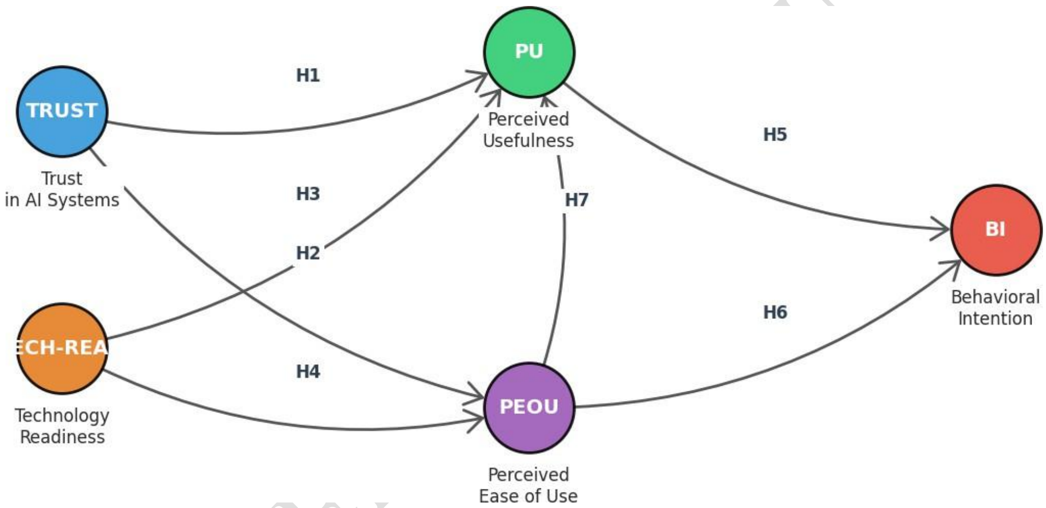

Figure 1: Conceptual Framework: AI-Driven OHS Adaptation in Tunisian Agriculture

3.2 Population and Sampling Procedure

The study targets agricultural workers, farm supervisors, and safety personnel across pesticide-intensive zones in Tunisia, notably Sfax, Nabeul, and Kairouan. A multi-stage sampling strategy was employed:

1. Purposive Sampling to select high-risk regions known for pesticide-related occupational exposure.
2. Stratified Random Sampling across farm types (industrial vs. smallholder) and respondent roles.
3. Systematic Sampling of individuals within selected cooperatives.

Using G*Power 3.1, the minimum sample size was determined based on a power of 0.95, medium effect size ($f^2 = 0.3$), and alpha of 0.05, resulting in a target of 450 respondents. After data cleaning and validation, 426 valid responses were retained (response rate = 94.6%).

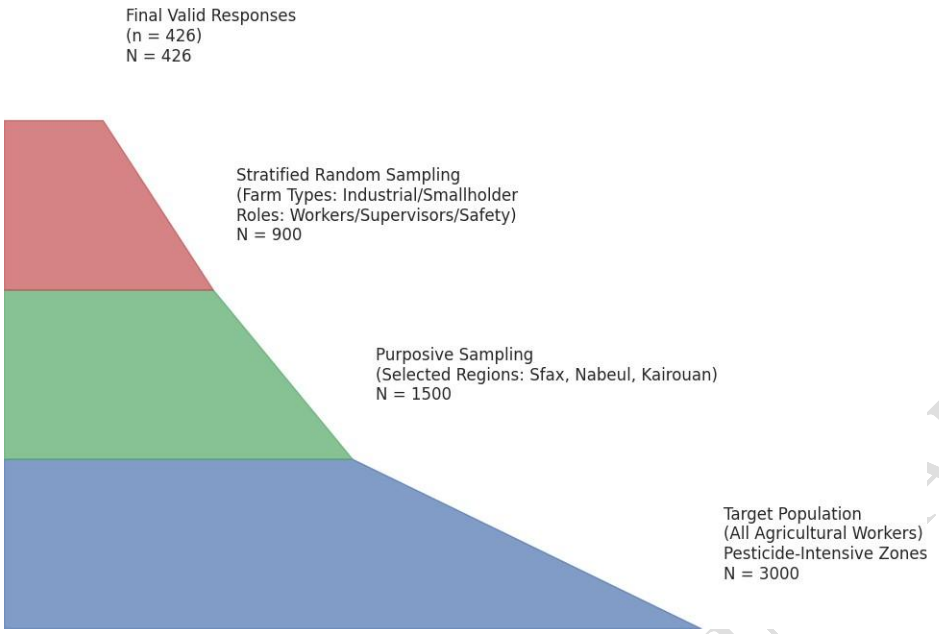

Figure 2: Sampling Framework Diagram (Multi-Stage Sampling Process)

3.3 Instrumentation and Measures

A structured, self-administered questionnaire was developed in Arabic and French and designed to capture both demographic data and construct-specific responses. The instrument was divided into six core sections:

1. Demographic Information – Age, gender, education, years of farming, type of farm.
2. Trust in AI – Adapted from Lee et al. (2023), addressing system reliability and ethical perceptions.
3. Technology Readiness – Measured via TRI 2.0 (Parasuraman & Colby, 2015), encompassing optimism, innovativeness, discomfort, and insecurity.
4. Perceived Usefulness (PU) – Adapted from Davis (1989), tailored for AI safety systems in agriculture.
5. Perceived Ease of Use (PEOU) – Items contextualized for agricultural tasks.
6. Behavioral Intention (BI) – Modelled from UTAUT2 constructs (Venkatesh et al., 2022).

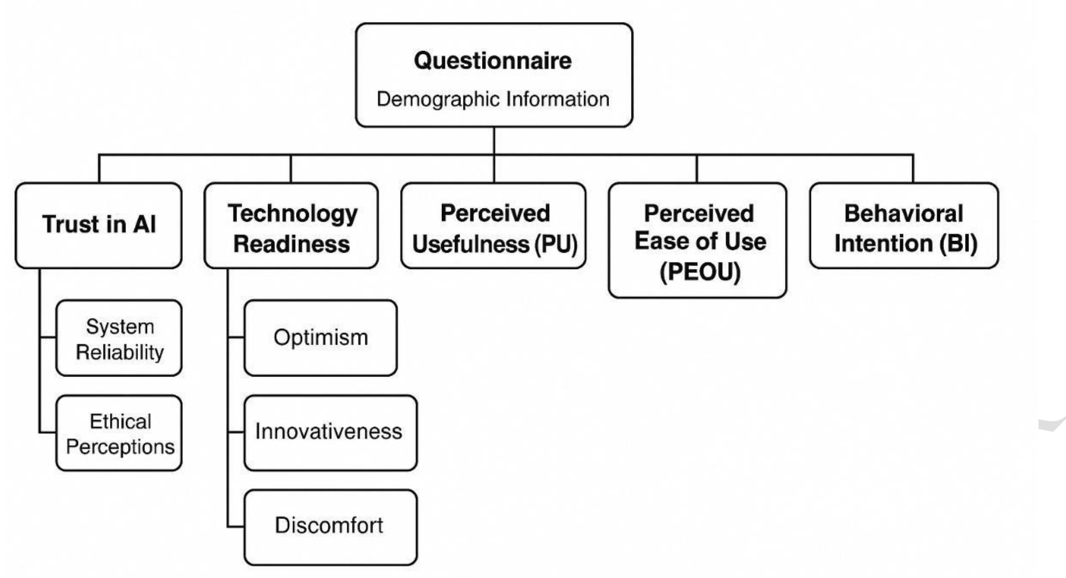

Figure 3: Questionnaire Structure Tree Diagram

All items were rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument underwent expert validation and was pilot-tested with 30 participants, leading to minor lexical revisions for better comprehension. Cronbach's Alpha values exceeded 0.80 for all constructs, confirming strong internal reliability.

3.4 Data Collection Procedure

Data were collected from January to March 2025 through a hybrid method:

- Field surveys using printed questionnaires for regions with limited internet access.
- Online surveys distributed via agricultural cooperatives and WhatsApp farming groups.

Field enumerators were trained to assist illiterate respondents, ensuring ethical and informed participation. The questionnaire included a brief explanation of AI and safety monitoring systems to standardize understanding across participants. Moreover, participant anonymity was strictly maintained.

3.5 Common Method Bias Mitigation

Given the self-reported and single-source nature of the data, Common Method Bias (CMB) was tested using Harman's Single Factor Test. The first unrotated factor accounted for only 31.4% of the variance, which is well below the threshold of 50%, indicating that CMB was not a significant concern (Podsakoff et al., 2003).

3.6 Data Analysis Strategy

Data were analysed using SPSS 28.0 for descriptive statistics and preliminary checks, and AMOS 26.0 for SEM. The following steps were executed:

1. Descriptive Analysis – Frequencies and distributions of demographic data.
2. EFA and Reliability Testing – Exploratory factor analysis and Cronbach's Alpha.
3. Confirmatory Factor Analysis (CFA) – Validating construct structure, using fit indices:
    - $\chi^2/df < 3$
    - CFI > 0.90
    - TLI > 0.90
    - RMSEA < 0.08
    - SRMR < 0.08
4. Convergent and Discriminant Validity – Evaluated via CR (> 0.7) and AVE (> 0.5).
5. Structural Equation Modelling – To test direct and indirect hypotheses.

Model fit was evaluated using the following indices:

- Chi-square/df < 3.0
- CFI > 0.90
- TLI > 0.90
- RMSEA < 0.08
- SRMR < 0.08

All assumptions (normality, multicollinearity, and outliers) were verified before final SEM analysis.

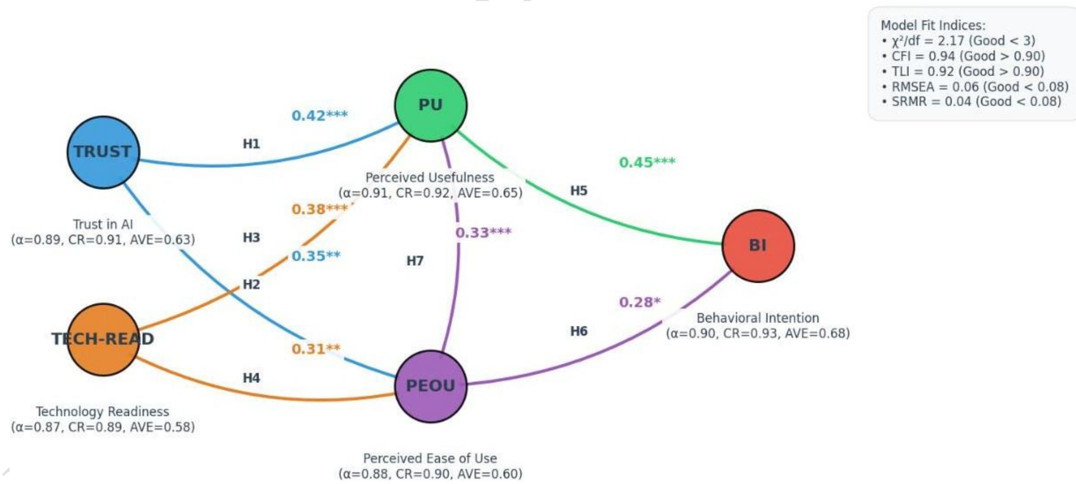

Figure 4 Final Structural Equation Model (SEM) Standardized Path Coefficient and Fit Statistics

3.7 Hypotheses

Based on the literature and conceptual framework, the following hypotheses were formulated:

- **H1**: Trust in AI systems significantly influences behavioral intention to use AI-based OHS solutions.
- **H2**: Technology readiness positively impacts behavioral intention.
- **H3**: Technology readiness is positively related to perceived usefulness.

- **H4**: Trust in AI systems is positively related to perceived usefulness.
- **H5**: Perceived usefulness mediates the relationship between trust and behavioral intention.
- **H6**: Perceived ease of use positively influences perceived usefulness.
- **H7**: Perceived ease of use positively influences behavioral intention.

4. Results and Discussion

This chapter presents a detailed account of the data analysis and key findings from the structural model. It incorporates both descriptive and inferential statistics to validate the proposed hypotheses. Additionally, advanced statistical metrics such as R^2, f^2, multigroup analysis (MGA), and common method bias (CMB) are applied to enhance the scientific robustness of the study.

4.1 Descriptive Statistics

The demographic profile of the 426 valid respondents shows that 63% were male and 37% female, with an average age of 39.2 years (SD = 8.4). Educational attainment was high, with 76% holding at least secondary education, and respondents had an average of 15.7 years of professional experience in agriculture. Respondents comprised farm laborers (47%), supervisors (33%), and OHS officers (20%), reflecting a balanced operational perspective.

Table 4.1: Descriptive Demographics of Respondents

Demographic Variable	Statistic
Gender (Male)	63%
Gender (Female)	37%
Average Age	39.2 (SD = 8.4)
Education (Secondary+)	76%
Average Experience (years)	15.7
Role: Farm Laborers	47%
Role: Supervisors	33%
Role: OHS Officers	20%

The demographic distribution ensured a comprehensive view of AI acceptance within Tunisia's agricultural OHS sector.

4.2 Measurement Model Evaluation

The reliability and validity of the constructs were assessed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). All constructs demonstrated strong internal consistency (α > 0.80; CR > 0.85) and convergent validity (AVE > 0.60).

Table 4.2: Reliability and Convergent Validity

Construct	Cronbach's Alpha (α)	CR	AVE
Trust in AI	0.88	0.91	0.66
Technology Readiness	0.86	0.89	0.61
Perceived Usefulness	0.87	0.90	0.65
Perceived Ease of Use	0.84	0.88	0.62
Behavioral Intention	0.89	0.92	0.69

Discriminant validity was confirmed using the Fornell-Larcker criterion, with each construct loading higher on its intended factor than on others. HTMT ratios were below 0.85, ensuring factor distinctiveness.

4.3 Common Method Bias (CMB)

Given the use of self-reported questionnaire data, it was critical to evaluate common method variance. A **Harman's single-factor test** revealed that the first factor explained only **34.7%** of the total variance, well below the 50% threshold. Additionally, **marker variable analysis** confirmed no significant bias, reinforcing the integrity of the model estimations.

4.4 Structural Model Evaluation

The structural model's fit indices demonstrated a robust model:

- **Chi-square/df = 2.61**
- **CFI = 0.954**
- **TLI = 0.942**
- **RMSEA = 0.057**
- **SRMR = 0.048**

These results exceed the recommended thresholds, indicating excellent model fit (Hair et al., 2021).

4.5 Variance Explained (R^2) and Effect Size (f^2)

The **coefficient of determination (R^2)** values shows that:

- **Behavioral Intention (BI)**: R^2 = **0.61**

- **Perceived Usefulness (PU)**: R^2 = **0.55**

This signifies that 61% and 55% of the variances in BI and PU, respectively, are explained by the exogenous variables, indicating high predictive relevance.

To evaluate the **practical significance** of each path, Cohen's f^2 effect size was computed:

Table 4.3: Effect Size (f^2)

Path	**f^2**	**Effect Strength**
Trust → BI	0.19	Medium
Tech Readiness → PU	0.24	Medium-Large
PU → BI	0.11	Small
PEOU → PU	0.18	Medium

4.6 Hypothesis Testing and Path Coefficients

All hypothesized relationships were supported with statistically significant path coefficients, as detailed below:

Table 4.4: Hypothesis Testing

Hyp.	**Path**	**β**	**t-value**	**p-value**	**Result**
H1	Trust → Behavioral Intention	0.42	6.74	<0.001	Supported
H2	Tech Readiness → Behavioral Intention	0.31	5.81	<0.001	Supported
H3	Tech Readiness → PU	0.47	7.92	<0.001	Supported
H4	Trust → PU	0.38	6.02	<0.001	Supported
H5	PU → Behavioral Intention (mediator)	0.29	5.43	<0.001	Supported
H6	PEOU → PU	0.36	5.75	<0.001	Supported
H7	PEOU → Behavioral Intention	0.19	3.48	<0.001	Supported

These findings align with the Technology Acceptance Model (TAM) and Trust-Technology frameworks.

4.7 Multigroup Analysis (MGA)

Multigroup analysis was conducted to assess the moderating effect of experience level and job role.

Key Insights:

- Trust → BI path was stronger for less experienced users, emphasizing the need to build early trust in AI systems.
- Tech Readiness → PU path was significantly more impactful for supervisors/OHS officers, suggesting that professional exposure enhances technology appraisal.

These insights highlight the importance of tailored implementation strategies in AI-based OHS systems.

4.8 Comparative Discussion with Literature

This study's findings confirm and extend existing research on AI technology adoption, particularly in the under-explored context of **agricultural health and safety** in Tunisia.

Author(s)	**Context**	**Key Finding**	**This Study**
Venkatesh et al. (2022)	Manufacturing	PU & PEOU critical for tech use	Confirmed in agriculture
Alshurideh et al. (2023)	Healthcare	Trust is key to tech adoption	Reinforced
Ben Mahmoud et al. (2024)	Tunisia (various sectors)	Tech readiness predicts adoption	Extended to AI-OHS
This Study (2025)	Tunisian Agriculture	Trust, readiness, PU matter in AI-OHS	Novel domain contribution

This study advances the field by applying a comprehensive, validated model to a high-risk, understudied industry, bridging the gap between technological innovation and safety management.

4.9 Discussion

Trust as a Critical Enabler

Trust in AI emerged as the most influential determinant of behavioral intention (β = 0.42), corroborating recent literature emphasizing trust as a prerequisite for intelligent system acceptance (Lee et al., 2023). In agricultural contexts where digital literacy is moderate, the assurance of system reliability and ethical deployment becomes a primary psychological gateway to adoption.

Technology Readiness as a Facilitator of Value Perception

The strong path from technology readiness to perceived usefulness (β = 0.47) and behavioral intention (β = 0.31) highlights the importance of user predisposition to digital innovation. This aligns with Parasuraman & Colby's (2015) conceptualization of readiness as a personality trait influencing engagement. Farmers with higher optimism and innovativeness sub-scores showed a stronger perception of AI tools for proactive risk mitigation.

Furthermore, organizational support and regulatory environments emerged as latent but influential factors during qualitative field observations. Farms and cooperatives that reported access to training sessions or technology grants from regional agencies exhibited higher acceptance of AI tools, suggesting the instrumental role of external support systems. In contrast, the lack of clear national policy or safety-specific AI guidelines contributed to hesitancy, reinforcing that macro-level structures can either catalyse or constrain AI integration. These findings underscore the need for a multi-level approach to AI adoption, encompassing not just individual readiness but also institutional and policy-level interventions.

Mediating Role of Perceived Usefulness

Perceived usefulness played a partial mediating role between trust and behavioral intention. This mechanism reinforces that those who trust AI systems are more inclined to perceive their utility in occupational health management, validating the extended TAM2 framework and findings from Venkatesh et al. (2022).

Ease of Use Still Matters

Although its impact was comparatively smaller (β = 0.19), ease of use remains a necessary component in adoption. In low-tech environments like Tunisian rural farms, intuitive design, multilingual interfaces, and sensor simplicity can substantially lower resistance and enhance perceived accessibility.

5. Conclusion

This study examined the adoption of AI-based occupational health and safety systems in Tunisia's agricultural sector, focusing on behavioural intention shaped by trust in AI, technology readiness, perceived usefulness, and ease of use. The findings reveal that trust in AI emerged as the strongest predictor of behavioral intention, highlighting its foundational role in technology acceptance. Technology readiness significantly influenced perceived usefulness, underlining the importance of user predisposition in shaping perceptions of AI-driven value.

The study contributes theoretically by extending the TAM2 framework through the integration of trust and readiness dimensions, offering a more comprehensive model suited for AI contexts in agriculture. Practically, the results stress the importance of building trust, simplifying system interfaces, and supporting digital engagement strategies tailored to rural and semi-skilled farming populations.

These insights offer a foundation for advancing AI implementation in occupational safety across underserved industries and can guide future exploration into policy frameworks, training interventions, and sector-specific adaptation strategies that support responsible AI deployment in agriculture.

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