

Awareness of Artificial Intelligence among Women in Algeria's Agrifood Industry

مستوى الوعي بالذكاء الاصطناعي لدى النساء العاملات في قطاع الصناعات الغذائية الزراعية بالجزائر

Naima BENKHIDER¹, Sonia KHERBACHI², Nassim KEDDARI³

¹ University of Bejaia, LRMTQ, FSECSG, Associate Researcher at CREAD, (Algeria),
naima.benkhider@univ-bejaia.dz

² University of Bejaia, LRMTQ, FSECSG, Associate Researcher at CREAD, (Algeria),
sonia.kherbachi@univ-bejaia.dz

³ University of Bejaia, FSECSG, Associate Researcher at CREAD, (Algeria),
nassim.keddari@univ-bejaia.dz

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Abstract:

Artificial intelligence (AI) is reshaping organizations, yet gender gaps in AI awareness may limit women's engagement, particularly in developing economies. This study examines AI awareness among women in organizations, using the Algerian agrifood sector as an empirical context. Data were collected via a perception questionnaire administered to 150 women. Descriptive statistics, Multiple Correspondence Analysis, Principal Component Analysis, and Partial Least Squares Structural Equation Modeling were used to analyze patterns of awareness and their determinants. The findings indicate generally low-to-moderate AI awareness and limited practical experience, alongside cautious optimism about AI's organizational benefits. AI awareness is driven primarily by experiential and attitudinal factors, actual AI use, perceived economic value, willingness to reskill, and perceived usefulness, rather than socio-demographic attributes or hierarchical position.

Keywords: Artificial intelligence awareness; AI literacy; Technology Acceptance Model; Gender; Emerging economies.

JEL Classification Codes : O33, J16, M15, Q13, O14

ملخص:

يُعِيد الذكاء الاصطناعي تشكيل المنظمات، غير أنّ الفجوات بين الجنسين في الوعي بالذكاء الاصطناعي قد تحدّ من مشاركة النساء، لا سيما في الاقتصادات النامية. تهدف هذه الدراسة إلى تحليل مستوى الوعي بالذكاء الاصطناعي لدى النساء العاملات في المنظمات، مع اعتماد قطاع الصناعات الغذائية الزراعية في الجزائر كإطار تطبيقي. جُمعت البيانات من خلال استبيان إداري وُزِعَ على 150 امرأة. وتم استخدام الإحصاءات الوصفية، وتحليل المراسلات المتعددة، وتحليل المكونات الرئيسية، ونموذج المعادلات الهيكلية باستخدام المربعات الصغرى الجزئية لدراسة أنماط الوعي ومحدداته. وتشير النتائج إلى مستويات منخفضة إلى متوسطة من الوعي بالذكاء الاصطناعي وخبرة تطبيقية محدودة، إلى جانب تفاؤل حذر بشأن الفوائد التنظيمية المحتملة للذكاء الاصطناعي. ويتحدد الوعي بالذكاء الاصطناعي أساساً بالعوامل التجريبية والاتجاهية، ولا سيما الاستخدام الفعلي، والقيمة الاقتصادية المتصورة، والاستعداد لإعادة التأهيل، والمنفعة المدركة، أكثر من ارتباطه بالخصائص الاجتماعية-الديموغرافية أو الموقع الوظيفي. كلمات مفتاحية: الوعي بالذكاء الاصطناعي؛ الثقافة في الذكاء الاصطناعي؛ نموذج قبول التكنولوجيا؛ النوع الاجتماعي؛ الاقتصادات الناشئة.

تصنيفات JEL: O14، Q13، M1، J16، O33.

Corresponding author: Naima BENKHIDER, e-mail: naima.benkhider@univ-bejaia.dz

INTRODUCTION:

Artificial intelligence is rapidly transforming economic systems and organizational practices across sectors such as healthcare, education, finance, and industry, driving productivity, innovation, and operational efficiency through automation, predictive analytics, and data-driven decision-making (Kalim, Kanwar, Sha, & Huang, 2025; Damerji & Salimi, 2021). However, the diffusion of AI tools is deeply embedded in existing structural inequalities, most notably gender-based disparities in digital skills, technological literacy, and participation in innovation processes (Russo, et al., 2025; Møgelvang, Bjelland, Grassini, & Ludvigsen, 2024). Global evidence consistently shows that women remain underrepresented in AI-related education, professional roles, and leadership positions, which limits their ability to benefit from AI-driven transformations fully and perpetuates the digital gender gap (Ozor, et al., 2025).

AI awareness is embedded within broader digital transformation processes that extend beyond technology adoption to encompass organizational structures, capabilities, and cultures (Benkhider & Kherbachi, 2021). Digital transformation theory emphasizes that the effective integration of advanced technologies depends on the alignment of technological infrastructure, human capabilities (Reggani et Benabid), and organizational readiness, rather than on technology deployment alone (Benkhider & Meziani, 2021). Within these frameworks, AI awareness emerges as a cognitive and contextual outcome of digital transformation, shaped by trust in AI use, attitudes toward AI use, trust in AI learning, and the organizational context in which AI technologies are embedded.

Understanding AI awareness, defined as individuals' recognition, understanding, and perceptual readiness toward AI tools, is essential for interpreting how diverse groups engage with AI systems in organizational contexts (Gui, Zhao, Ai, & Ouyang, 2025). Unlike adoption or use, awareness encompasses both cognitive recognition of AI capabilities and attitudinal readiness to engage with them, shaping early stages of commitment that precede formal acceptance and use. In technology research, awareness can serve as a cognitive precursor that influences the formation of perceptions of usefulness and ease of use, which are central determinants of behavioral intention in established models such as the Technology Acceptance Model (TAM) (Aiello, Melone, & Russo, 2026; Davis, 1989). From this perspective, individuals' initial awareness conditions their ability to interpret, evaluate, and trust AI technologies, thereby mediating how organizational investments in digital innovations translate into actual commitment to AI (Russo, et al., 2025).

Although prior research has extensively documented gender differences in attitudes toward artificial intelligence, highlighting higher levels of AI anxiety (Kwak, Ahn, & Seo, 2022), ethical concern (Bogdadi, Qushmaq, Baeshen, & Aljeaid, 2025), and lower usage (Aldasoro, Armantier, Doerr, Gambacorta, & Oliviero, 2024) among women, and has identified structural, socio-cultural, and educational barriers constraining women's engagement with AI technologies (Kalim, Kanwar, Sha, & Huang, 2025; Belas, Kliestik, Dvorsky, & Streimikiene, 2025), this literature remains predominantly outcome-oriented. Existing studies focus primarily on adoption behaviors, skill gaps, or policy prescriptions. At the same time, AI awareness is primarily treated as an implicit antecedent rather than a theoretically specified construct shaping early cognitive and attitudinal engagement with AI systems.

While recent contributions underscore the empowering potential of AI for women in domains such as education, healthcare, entrepreneurship, and work–life balance (Mahalakshmi

& Jayanthiladevi, 2024; Ebrahimi, et al., 2024; Meharunisa, Almugren, Sarabdeen, Mabrouk, & Kijas, 2024), and emphasize the role of digital literacy and inclusive institutional frameworks in narrowing gender-based disparities (Kalim, Kanwar, Sha, & Huang, 2025), limited attention has been paid to AI awareness as a cognitive precursor shaping perceived usefulness, trust, and attitudes toward AI. From a TAM perspective, this omission constrains theoretical understanding of how women form initial perceptions of AI prior to adoption, particularly within organizational digital transformation processes in emerging economies and unevenly digitized sectors. Addressing this gap is essential for advancing theory on early-stage technology engagement and for informing inclusive digital transformation strategies grounded in cognitive readiness rather than post-adoption outcomes.

In response to the limited theorization of Artificial Intelligence awareness as a distinct cognitive and attitudinal construct, this study aims to explore and explain how AI awareness is formed and structured among women working in the Algerian agrifood industry. Rather than focusing on adoption outcomes, the study emphasizes early-stage engagement, **examining how experiential exposure, organizational context, and perceived implications of AI shape awareness in a sector characterized by partial and uneven digital transformation.**

Guided by a theory-informed exploratory-explanatory approach, the study addresses the following research questions:

RQ1. What is the level of AI awareness among women in the Algerian agrifood industry?

RQ2. How is AI awareness structured in cognitive, attitudinal, and experiential terms?

RQ3. How do experiential and organizational factors relate to AI awareness?

RQ4. Do AI awareness structures differ between managers and employees?

In line with these questions, three exploratory hypotheses are proposed:

H1. AI awareness is significantly associated with experiential engagement with AI technologies within organizations.

H2. Organizational role influences the configuration of AI awareness, leading to distinct patterns of awareness among managers and employees.

H3. AI awareness encompasses both perceived opportunities and perceived risks, which are expected to coexist within awareness structures rather than forming a linear pattern of acceptance or resistance.

This research contributes to the literature by highlighting AI awareness as a unique cognitive precursor and tackling its under-theorization in previous gender- and AI-focused studies. The agrifood sector offers a pertinent empirical context in which AI adoption is inconsistent due to infrastructural limitations, skill shortages, and organizational resistance, factors that disproportionately affect women. This setting thus allows for a targeted exploration of how early perceptions, attitudes, and awareness of AI influence technology acceptance in emerging economies with uneven digital development.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on AI awareness, AI literacy, gender and technology, and technology acceptance models, and develops an integrated conceptual framework. Section 3 outlines the research methodology, detailing the data collection process, measurement instruments, and the multi-stage analytical approach adopted in the study. Section 4 presents the empirical results, including descriptive statistics, exploratory analyses, and structural modeling outcomes. Section 5 discusses these

findings in relation to existing theory and highlights their theoretical and managerial implications. Finally, Section 6 concludes the paper by summarizing the main contributions, acknowledging limitations, and suggesting directions for future research.

1- Literature review:

Awareness of Artificial Intelligence has become a critical factor in shaping how individuals engage with emerging technologies, particularly in sectors undergoing rapid digital transformation, such as the agrifood industry, healthcare, education, manufacturing, and financial services (Bogdadi, Qushmaq et Baeshen; Benzitouni et Naamane). Understanding AI awareness among women in Algeria requires integrating technical, cognitive, educational, socio-ethical, and gendered perspectives. This section reviews current literature on AI awareness, highlighting conceptual frameworks, gender differences, literacy, adoption barriers, and empowerment opportunities to provide an exploratory understanding of how women perceive and interact with AI in professional contexts.

Conceptualizing AI awareness requires moving beyond vague discussions of “intelligent systems” toward explicit, measurable constructs that capture both AI systems’ capacities and human users’ understanding, perceptions, and reflections about AI technologies (Kalim, Kanwar, Sha, & Huang, 2025). Recent research distinguishes AI awareness from philosophical notions of consciousness or personhood, positioning it as a functional, operational capacity rather than a metaphysical phenomenon. Recent systematic reviews conceptualize AI awareness as a multidimensional construct encompassing cognitive understanding, attitudinal readiness, ethical reflection, and contextual evaluation, highlighting that awareness can be operationalized and empirically assessed rather than treated as an abstract or purely technical property (Zhu & Wan Hussain, 2025). Philosophical analyses similarly differentiate functional self-modeling from phenomenal consciousness, noting that AI may mimic aspects of self-awareness without possessing human-like subjectivity (Bogdadi, Qushmaq, Baeshen, & Aljeaid, 2025). These insights emphasize that awareness can be operationally defined, evaluated, and designed, providing a valuable lens to assess human understanding of AI in organizational and sectoral contexts.

At the human level, AI awareness is closely linked to AI literacy, encompassing the knowledge, skills, and critical understanding necessary to use, evaluate, and ethically navigate AI systems (Ng, Leung, Chu, & Qiao, 2021). Multidimensional frameworks identify several key components, including cognitive and technical understanding (concepts, data, algorithms), practical application (ability to use AI tools effectively), critical evaluation and creation (assessing and designing AI responsibly), and ethical and socio-emotional awareness (understanding societal impacts, biases, and risks) (Zhu & Wan Hussain, 2025). Empirical studies show that structured literacy interventions improve both understanding and empowerment, emphasizing that awareness entails knowledge and agency (Ebrahimi, et al., 2024). Within the agrifood industry, such literacy is essential for enabling women to engage with AI applications like precision agriculture, supply chain optimization, and data-driven decision-making.

AI literacy and ethical-reflexive awareness are essential components of comprehensive AI awareness. Beyond technical knowledge, AI literacy includes the ability to understand, critically evaluate, and responsibly apply AI technologies, while ethical-reflexive awareness emphasizes recognizing biases, societal impacts, and responsible development practices

(Damerji & Salimi, 2021; Bogdadi, Qushmaq, Baeshen, & Aljeaid, 2025). Integrating these dimensions ensures that AI awareness encompasses both cognitive competence and socio-ethical judgment, fostering informed, responsible, and equitable engagement with AI, particularly in professional environments in which gendered dynamics shape access and participation.

Gendered research consistently highlights pronounced differences in attitudes toward AI, with women reporting higher AI-related anxiety, lower AI use, and stronger ethical concerns than men (Russo, et al., 2025; Aldasoro, Armantier, Doerr, Gambacorta, & Oliviero, 2024). These differences are shaped by socio-cultural norms, educational disparities, and systemic biases that constrain women's access to AI-related opportunities (Møgelvang, Bjelland, Grassini, & Ludvigsen, 2024; Aiello, Melone, & Russo, 2026). The TAM provides a valuable framework for understanding how these factors influence adoption behaviors. According to TAM, perceived usefulness and perceived ease of use are key determinants of an individual's intention to adopt technology (Davis, 1989). In gendered contexts, women may perceive AI tools as more challenging to use and less applicable to their work, which can reduce both engagement and adoption intentions.

Integrating TAM with the concept of AI literacy allows for a more nuanced understanding of these dynamics. AI literacy, encompassing cognitive, technical, ethical, and socio-emotional competencies, directly shapes perceptions of ease of use and usefulness. Women with higher AI literacy are more likely to understand AI functionalities, apply tools effectively, and critically evaluate their relevance to professional tasks, thereby enhancing both perceived usefulness and ease of use. Conversely, gaps in AI literacy can reinforce feelings of anxiety and reduce trust, negatively affecting TAM constructs and limiting adoption.

Addressing these challenges requires interventions that simultaneously develop technical knowledge, ethical awareness, and practical competencies. Inclusive training programs, mentorship, and policies that provide equitable access to AI tools can strengthen AI literacy, which in turn positively influences TAM constructs. By fostering both cognitive and socio-emotional understanding of AI, organizations can enhance women's awareness, engagement, and responsible adoption of AI technologies, creating a pathway from knowledge acquisition to practical application and ethical deployment.

Despite these challenges, AI presents significant opportunities for empowerment. Studies show that AI can enhance education, healthcare, entrepreneurship, and work-life balance for women (Ebrahimi, et al., 2024; Mahalakshmi & Jayanthiladevi, 2024). In organizational and sectoral contexts, awareness of AI shapes perceptions of capabilities, risks, and potential benefits. For example, in hospitality, awareness of AI adoption influences employees' perceived job security and engagement strategies (Kwak, Ahn, & Seo, 2022), while in education, AI literacy affects students' critical thinking and self-efficacy (Møgelvang, Bjelland, Grassini, & Ludvigsen, 2024). In agrifood, such awareness can empower women to leverage AI to improve operational efficiency, drive innovation, and gain a competitive advantage.

Synthesizing these perspectives, AI awareness emerges as a multilevel construct. At the system level, it reflects AI architectures with metacognitive, self, social, and situational capacities (Iddrisu, Iddrisu, & Aminu, 2025). At the human level, it aligns with AI literacy and critical consciousness: the ability to understand, use, judge, and ethically navigate AI in specific

practices (Bogdadi, Qushmaq, Baeshen, & Aljeaid, 2025). At the organizational and societal levels, it encompasses shared perceptions of AI's value, risks, and governance implications, influencing employment, education, and policy responses (Kalim, Kanwar, Sha, & Huang, 2025). Incorporating gendered insights and TAM constructs, this integrated view highlights that knowledge, attitudes, systemic barriers, perceived usefulness, and ethical engagement shape women's awareness in the Algerian agrifood sector. Enhancing AI awareness thus requires coordinated interventions across educational, organizational, and policy domains to build capacity, trust, and equitable access.

2-Research Methodology :

This study adopts a quantitative, multistage analytical design to examine women's awareness of Artificial Intelligence (AI) in the Algerian agrifood industry.

1-1 Research Design and Analytical Strategy

Given the heterogeneous nature of AI adoption, the research design intentionally integrates demographic variables, qualitative categorical indicators, and Likert-scale measures of awareness within a single empirical framework. This combination enables a nuanced understanding of AI awareness that captures not only attitudinal evaluations but also contextual and structural conditions shaping AI tools' exposure.

To ensure methodological rigor and theoretical coherence, the analysis follows a sequential logic. First, descriptive statistics are employed to summarize respondent characteristics and baseline perceptions. Second, Multiple Correspondence Analysis (MCA) is applied to explore the global structure of AI awareness across mixed categorical and ordinal variables. Third, Principal Component Analysis (PCA) is conducted separately for managers and employees to uncover role-specific latent awareness structures. Finally, Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to test hypothesized relationships among latent constructs and to assess the relative contribution of AI usage, perceived benefits, and employment-related concerns to overall AI awareness.

This layered analytical approach enhances rigor by combining exploratory, comparative, and confirmatory techniques, thereby mitigating the limitations associated with relying on a single statistical method.

1-2 Population, Sampling, and Data Collection

The study population consists of women employed in agrifood firms located in Bejaia, Algeria, a region characterized by a high concentration of agrifood activities spanning production, processing, packaging, logistics, and commercialization. A purposive sampling strategy was adopted to ensure representation across organizational hierarchies and functional domains. The final sample comprises 150 respondents, including 55 managers and 95 employees, allowing meaningful comparison between strategic and operational perspectives.

Data were collected using a structured perception questionnaire (Ng, Leung, Chu, & Qiao, 2021) administered between February and June 2025, in collaboration with company human resource departments. Participation was voluntary, anonymous, and subject to informed consent. Ethical approval was obtained from the University of Bejaia Research Ethics Committee and the Research Center in Applied Economics for Development (CREAD).

1-3 Measurement Instrument

The questionnaire was designed to capture **three complementary layers of AI awareness**:

- a. **Demographic and Professional Variables** (Q4–Q11), including age, hierarchical level, years in the company, position tenure, company size, and activity. These variables were used to describe the sample and to examine potential moderating effects in subsequent analyses.
- b. **Qualitative and Categorical Indicators**, capturing concrete AI exposure and organizational decision contexts, were incorporated to distinguish symbolic awareness from actual engagement. These include AI task usage (*Q13_ai_use_tasks*), AI technologies used (*Q14_ai_tech_used*), system integration (*Q15_ai_system_integration*), decision-making collaboration (*Q17_decision_collab_level*), and so on.
- c. **Perceptual Constructs** capturing digital literacy, formed the core analytical layer, measured on five-point Likert scales (1 = strongly disagree; 5 = strongly agree), capturing AI awareness (*Q12_ai_awareness*), familiarity (*Q39_familiar_with_ai*), task integration, AI literacy, perceived business impact, efficiency gains (*Q46_ai_efficiency_gain*), cost reduction, job reduction perception, and readiness for job change and reskilling (*Q52_reskill_willingness*).

Together, these three layers ensure a comprehensive operationalization of AI awareness that integrates contextual characteristics (*who the respondents are*), experiential exposure (*what they actually do with AI*), and subjective evaluations (*their awareness of AI*). This structured measurement approach provides a strong methodological foundation for the combined use of descriptive statistics, MCA, PCA, and OLS-SEM.

1-4 Moderators

In line with the Unified Theory of Acceptance and Use of Technology (UTAUT), demographic and organizational variables were not treated as mere statistical controls but were theoretically positioned as contextual moderators that shape perceptions of AI awareness and adoption. Prior research suggests that age, professional experience, hierarchical authority, and organizational context systematically influence technology acceptance by affecting cognitive adaptation, decision autonomy, and access to resources. Accordingly, the present study integrates demographic variables as structural conditioning factors rather than nuisance covariates (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012), as presented in Table 1.

Table (1): Key Moderator Variables and Theoretical Significance

Variable	Questionnaire Code	Theoretical Role
Age	Q4_age	Experience and cognitive adaptation
Hierarchy Level	Q6_hierarchy_level	Decision power and strategic influence
Years in Company	Q7_years_company	Accumulated organizational capital
Years in Position	Q8_years_position	Task specialization and role stability
Company Size	Q11_company_size	Resource availability and AI readiness
Company Activity	Q10_company_activity	Functional relevance of AI adoption

Source: Elaborated by authors

By integrating these variables as moderators, the model accounts for heterogeneity in AI awareness arising from individual career trajectories and organizational environments, consistent with UTAUT and human capital perspectives.

1-5 Data Analysis

All statistical analyses were conducted using R software (version 4.3), following a multi-stage analytical framework designed to ensure methodological rigor and theoretical relevance

in studying AI awareness among women in the Algerian agrifood sector. The analytical progression moved from exploratory data reduction to predictive causal modeling, aligning with established practices in technology adoption and gender-inclusive research (Venkatesh et al., 2016; Hair et al., 2021).

Initial descriptive statistics, including means, standard deviations, frequencies, and cross-tabulations, were computed to profile the sample and summarize baseline AI perceptions. This foundational step is critical in gender-technology studies for contextualizing respondents within the broader workforce and identifying preliminary distributional patterns that may inform subsequent analyses (Field, 2018).

To uncover latent structures within categorical and ordinal AI awareness variables, Multiple Correspondence Analysis (MCA) was applied to the full dataset. MCA is particularly suited for visualizing high-dimensional categorical data and identifying associative patterns across response categories, offering a geometric representation of perceptual configurations (Greenacre & Blasius, 2006). By mapping the collective cognitive and attitudinal orientations of women toward AI, MCA provided a holistic view of the awareness landscape, setting the stage for more focused, construct-based analysis (Le Roux & Rouanet, 2010).

Given the interrelated nature of Likert-scale perception items and the expected differences by role in AI exposure and responsibility, PCA was performed separately for managers ($n = 55$) and employees ($n = 95$). Conducting PCA tailored to each subgroup is justified in organizational research, especially when hierarchical differences in technology perception remain underexplored (Tarhini et al., 2017). This method ensured the resulting components were psychometrically valid for each group, avoided aggregation bias, and allowed detailed, role-specific insights.

To examine predictive and causal relationships among the AI awareness constructs derived from PCA, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. PLS-SEM is particularly appropriate for exploratory research, complex models with small to moderate sample sizes, and data that may not meet strict multivariate normality assumptions (Hair et al., 2021). Its ability to handle both reflective and formative constructs, coupled with its strength in prediction-oriented modeling, makes it especially suitable for studying emerging phenomena such as AI awareness in under-researched, context-specific settings (Henseler et al., 2016). In this study, PLS-SEM was used to test hypotheses on how organizational support, digital literacy, and AI-related perceptions jointly influence AI awareness and behavioral intentions among women, thereby addressing a significant gap in the literature on gender-inclusive technology diffusion within agrifood systems.

In this analytical sequence, MCA and PCA were used for dimensional exploration, whereas PLS-SEM served as a complementary structural approach to validate and quantify inter-construct relationships.

The following section presents the results, structured according to the analytical framework, highlighting demographic patterns, perceptual structures, and causal relationships in AI awareness.

3-Research Results:

This section presents the study's empirical findings following a structured analytical progression. First, descriptive statistics provide an overview of the sample characteristics and key AI-related variables. Second, exploratory analyses, including MCA and PCA, uncover

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latent perceptual structures underlying AI awareness and examine potential role-based differences. Third, the measurement model of the PLS-SEM is assessed for reliability and convergent validity, with particular attention to the heterogeneous nature of AI usage. Finally, the structural model results identify the main determinants of AI awareness among women in the Algerian agrifood sector.

3-1 Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables included in the analysis, encompassing demographic characteristics, AI awareness and usage, perceived organizational integration, anticipated business impacts, and career-related perceptions.

Table (2): Descriptive Statistics

	Min	Max	Mean	Standard Deviation
age	1	7	4,03	1,548
Experience	1	4	1,95	,968
seniority	1	4	1,97	,972
AI_awareness	1,0	5,0	2,500	1,2849
AI_tasks	1,0	4,0	2,056	1,1396
AI_integration	1,0	5,0	2,377	1,0782
decision_collab_level	1,0	5,0	2,370	1,1863
AI_impact_production	1,0	5,0	2,870	1,1824
AI_impact_logistics	1,0	5,0	2,741	1,0848
AI_impact_sales	1,0	5,0	3,093	1,1699
AI_impact_marketing	1,0	5,0	3,574	1,1427
AI_impact_HR	1,0	5,0	2,537	1,1445
AI_cost_reduction	1,0	5,0	2,704	1,2229
AI_job_reduction	1,0	5,0	2,204	1,1054
AI_Familiarity	1,0	5,0	2,158	1,2490
AI_tasks_employee	1,0	5,0	2,137	1,3258
AI_efficiencies	1,0	5,0	2,863	1,2933
Job_change_readiness	1,0	5,0	2,842	1,3153
Reskill_willingness	1,0	5,0	3,168	1,3888

Source : Elaborated by authors

Respondents are predominantly mid-aged ($M = 4.03$ on a 1–7 scale, $SD = 1.55$) and report relatively limited professional tenure, both within their organizations ($M = 1.95$, $SD = 0.97$) and in their current positions ($M = 1.97$, $SD = 0.97$). This profile suggests a workforce that is still consolidating professional experience, potentially affecting exposure to strategic digital initiatives and access to advanced AI-related training opportunities.

Overall levels of AI awareness remain modest ($M = 2.50$, $SD = 1.28$). This low awareness is accompanied by limited integration of AI into daily tasks ($M = 2.06$, $SD = 1.14$) and weak perceived compatibility between AI technologies and existing organizational systems ($M = 2.38$, $SD = 1.08$). In addition, perceived collaboration among management, IT departments, and operational units is low ($M = 2.37$, $SD = 1.19$), pointing to constrained cross-functional coordination in AI-related initiatives, an important organizational barrier to effective adoption.

Respondents perceive AI as having a more substantial impact on customer-facing functions, particularly marketing ($M = 3.57$, $SD = 1.14$) and sales ($M = 3.09$, $SD = 1.17$). In contrast, perceived impacts on internal functions remain moderate, including human resources ($M = 2.54$, $SD = 1.14$), cost reduction ($M = 2.70$, $SD = 1.22$), production ($M = 2.87$, $SD = 1.18$), and logistics ($M = 2.74$, $SD = 1.08$). These patterns suggest that AI is currently framed more as a market-oriented tool than as a driver of internal efficiency or operational optimization within the agrifood sector.

Concerns regarding job reduction due to AI are present but remain limited ($M = 2.20$, $SD = 1.11$). At the same time, respondents express a relatively strong willingness to reskill ($M = 3.17$, $SD = 1.39$) and a moderate readiness to change jobs if required ($M = 2.84$, $SD = 1.32$). Despite this openness to adaptation, familiarity with AI technologies ($M = 2.16$, $SD = 1.25$) and task-level engagement ($M = 2.14$, $SD = 1.33$) remain low, revealing a gap between adaptive intentions and actual exposure or use.

Complementary t-tests indicate that most mean values differ significantly from the scale midpoint ($p < 2.2 \times 10^{-16}$), confirming that these patterns reflect systematic perceptions rather than random variation.

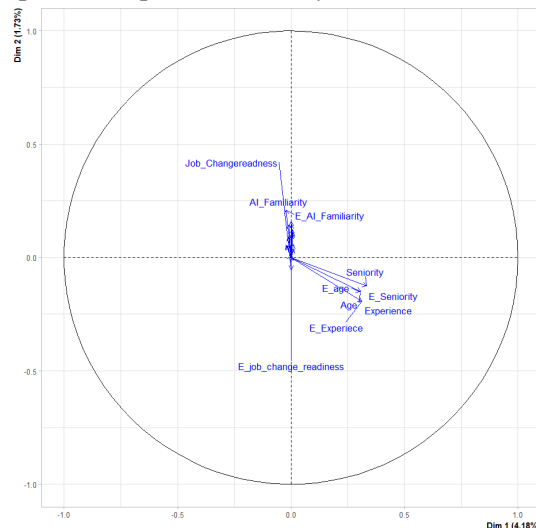
3-2 Exploratory Structure of AI Awareness (MCA and PCA)

To uncover the latent structure of AI awareness and to examine whether perceptual patterns differ by organizational role, exploratory analyses were conducted prior to structural modeling.

3.2.1 Structure of AI Awareness: Multiple Correspondence Analysis

A Multiple Correspondence Analysis was applied to the full sample ($N = 150$) to examine how AI-related perceptions are organized. Although the first two dimensions account for a modest proportion of total inertia, consistent with attitudinal research, their interpretation is theoretically meaningful, as illustrated in Figure 1.

Figure (1): Multiple Correspondence Analysis of the Structure of AI Awareness



Source: Elaborated by authors

The first dimension (4.18% of inertia) represents a general orientation toward AI. It contrasts respondents characterized by low AI understanding, weak task integration, limited trust, and skepticism regarding organizational compatibility with those reporting higher perceived usefulness, stronger learning intentions, and greater readiness for AI integration. This dimension captures a continuum of AI awareness grounded in evaluative and behavioral

orientations rather than demographic attributes, closely aligning with technology acceptance mechanisms.

The second dimension (1.73% of inertia) reflects divergent expectations regarding the consequences of AI adoption. One pole emphasizes anticipated productivity gains and functional improvements, particularly in marketing and sales. In contrast, the opposite pole is dominated by concerns related to job displacement, automation risks, and reduced human collaboration. This dimension reflects the tension between AI optimism and AI-related anxiety widely discussed in the future-of-work literature.

The factorial configuration shows a tight cluster of AI awareness, perceived usefulness, trust, willingness to reskill, and career adaptability, indicating that AI awareness forms a coherent noncognitive structure. In contrast, demographic variables such as age, tenure, and occupational category cluster near the origin, suggesting limited explanatory power in structuring AI awareness.

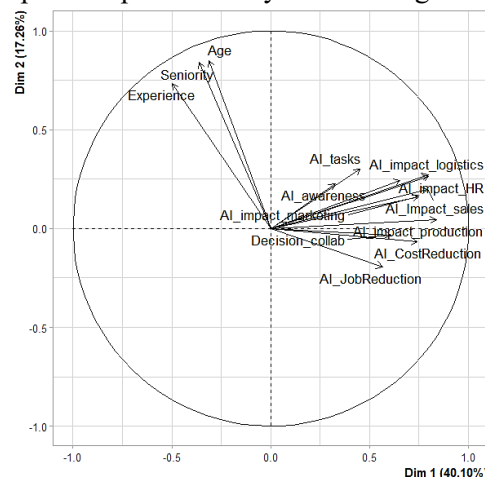
3.2.2 Principal Component Analysis by Organizational Role

To assess whether these perceptual structures vary by hierarchical position, separate PCAs were conducted for managers and employees.

a. Managerial Perception: PCA (N = 55)

Two components emerged from the analysis (Figure 2). The first component explains 40.10% of the variance. It is defined by AI awareness, task integration, perceived usefulness across organizational functions (production, logistics, marketing, sales, and HR), as well as expectations related to cost reduction and job displacement. This configuration reflects a strategic evaluation of AI that integrates anticipated benefits and perceived risks into a unified judgment. The second component (17.26%) is primarily associated with demographic variables and remains largely orthogonal to AI-related perceptions.

Figure (2): Principal Component Analysis of Managerial Perceptions of AI

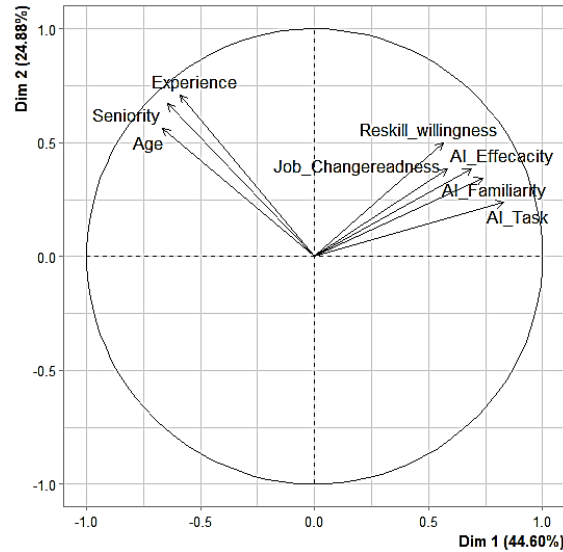


Source: Elaborated by authors

b. Employees' Perception PCA (N = 95)

For employees, the first component, illustrated in Figure.3, explains 44.60% of the variance and is dominated by AI familiarity, perceived ability, task integration, willingness to reskill, and readiness to change jobs. This component reflects a learning- and adaptability-oriented orientation toward AI. The second component (24.90%) captures a weaker demographic gradient linked to age and professional experience.

Figure (3): Principal Component Analysis of Employees' Perceptions of AI



Source: Elaborated by authors

Taken together, these analyses indicate that while AI perceptions in both groups are primarily attitudinal, managers frame AI through a strategic and organizational lens. In contrast, employees anchor their perceptions in adaptability, skill development, and employability.

3-3 Measurement Model Assessment (PLS-SEM)

Prior to testing the structural relationships, the measurement model was assessed for reliability and convergent validity.

3-3-1 Reliability and Convergent Validity

Table 3 reports the reliability and convergent validity indicators for the latent constructs included in the PLS-SEM measurement model, namely Cronbach's alpha (α), composite reliability (rhoC), average variance extracted (AVE), and rhoA.

Table (3): Construct Reliability and Validity Metrics

Variable	Alpha	RhoC	AVE	RhoA	Interpretation
AI_Familiarity	1.0	1.0	1.0	1.0	Perfect reliability
AI_Usage	0.0	0.574	0.574	1.148	Problematic: Alpha is too low (<0.7), rhoC below threshold, AVE >0.5. Needs attention.
AI_System_Integration	1.0	1.0	1.0	1.0	Perfect reliability
Decision_Collaboration	1.0	1.0	1.0	1.0	Perfect reliability
AI_Business_Impact	0.911	0.908	0.711	1.180	Excellent reliability
Others	1.0	1.0	1.0	1.0	Perfect reliability

Source : Elaborated by authors

Overall, the results indicate strong measurement properties for most constructs. AI Familiarity, AI System Integration, Decision Collaboration, and the group of other constructs all exhibit perfect reliability, with α , rhoC, rhoA, and AVE equal to 1.00. These values indicate complete internal consistency and full convergence of the associated indicators, confirming that these constructs are measured stably and unambiguously.

The AI Business Impact construct also demonstrates excellent reliability and convergent validity, with Cronbach's alpha ($\alpha = 0.911$), composite reliability (rhoC = 0.908), and rhoA (1.180) well above the recommended threshold of 0.70, and an AVE of 0.711 exceeding the minimum criterion of 0.50. These results suggest that the indicators associated with this

construct share a substantial proportion of variance and reliably capture perceived AI-related business outcomes.

In contrast, the AI Usage construct exhibits atypical reliability patterns. Cronbach's alpha is equal to zero, and composite reliability ($\rho_C = 0.574$) falls below the conventional threshold, while AVE remains acceptable (0.574). This configuration indicates limited internal consistency among the indicators but adequate convergent validity. Rather than indicating a measurement deficiency, this pattern reflects substantial behavioral heterogeneity in AI usage among respondents. AI usage spans a wide range of practices, from non-use to advanced engagement with multiple AI tools, and varies across hierarchical roles, task domains, and decision rationales. Such diversity violates the assumption of homogeneity underlying reflective measurement models and naturally constrains reliability coefficients.

Taken together, the results suggest that, except for AI Usage, which captures multidimensional, unevenly distributed behavior, the measurement model demonstrates strong reliability and convergent validity. In line with PLS-SEM's predictive and exploratory orientation, retaining the AI Usage construct is methodologically justified, particularly given its theoretical relevance and significant role in the structural model.

3-3-2 Assessment of AI_Usage Construct Heterogeneity

The AI_Usage construct exhibits lower internal consistency while maintaining acceptable convergent validity ($AVE > 0.50$). This pattern reflects empirical heterogeneity rather than a measurement deficiency. AI usage ranges from complete non-use to advanced engagement with multiple tools (e.g., ERP systems, business intelligence, and generative AI). It varies systematically by hierarchical role, tenure, task domain, and decision rationale.

Such diversity indicates that AI usage in this context is multidimensional and behaviorally fragmented, characteristics typical of emerging and uneven technological adoption environments. In line with the predictive and exploratory orientation of PLS-SEM, retaining theoretically meaningful constructs that capture heterogeneous behaviors is methodologically justified.

4.4 Determinants of AI Awareness: Structural Equation Modeling Results

The structural model explains a moderate share of variance in AI awareness ($R^2 = 0.370$; adjusted $R^2 = 0.329$), which is considered acceptable in behavioral and technology adoption research (Hair et al., 2022). According to established guidelines by Hair et al (2022), R^2 values of 0.25–0.50 indicate moderate explanatory power, suggesting the model captures a meaningful share of the factors shaping women's AI awareness in the Algerian agrifood industry.

Consistent with this level of explanatory power, effect sizes were evaluated using the f^2 thresholds outlined by Hair et al. (2022). These thresholds suggest that 0.02 indicates a small effect, 0.15 a medium effect, and 0.35 a significant effect, as shown in Table 4.

Table (4): Path Coefficients and Effect Sizes (f^2) for the AI Awareness Model

Predictor Construct	β	f^2	Effect Size
AI Usage	0.543	≥ 0.35	Large
AI System Integration	0.036	< 0.02	Negligible
Decision Collaboration	-0.036	< 0.02	Negligible
AI Business Impact	-0.014	< 0.02	Negligible
Efficiency Gain	0.000	< 0.02	Negligible
Cost Reduction	0.247	$0.02 - < 0.15$	Small

Job Reduction Perception	-0.144	0.02–<0.15	Small
Job Change Readiness	0.000	<0.02	Negligible
AI Familiarity	0.000	<0.02	Negligible

Source : Elaborated by authors

According to the framework in Figure 4 and the results in Table 4, AI usage is the most influential determinant of AI awareness ($\beta = 0.543$), with a large effect size ($f^2 \geq 0.35$). This result highlights the central role of hands-on interaction with AI technologies in shaping awareness and understanding. Perceived cost reduction also positively and significantly influences AI awareness ($\beta = 0.247$), corresponding to a small effect size ($0.02 \leq f^2 < 0.15$). This finding underscores the relevance of tangible economic benefits in reinforcing AI awareness, particularly in resource-constrained organizational contexts such as the agrifood sector. In contrast, the perception of job reduction is negatively associated with AI awareness ($\beta = -0.144$), with a small effect size, indicating a limited but non-negligible contribution to the explained variance in AI awareness.

Figure (4): Structural Model of Factors Influencing AI Awareness



Source: Elaborated by authors

Other constructs, including AI familiarity, system integration, decision collaboration, perceived business impact, efficiency improvements, and job change readiness, show weak or nonsignificant effects, with effect sizes below the practical relevance threshold.

Awareness of Artificial Intelligence among Women in Algeria's Agrifood Industry

a. Exploratory Analysis of Usage Heterogeneity

To further understand the low internal consistency observed for the AI Usage construct, an exploratory analysis was conducted to identify sources of response heterogeneity. Table 5 summarizes the main dimensions of heterogeneity identified in the data and their observed impact on reliability.

Table (5): Empirical Sources of AI Usage Heterogeneity Affecting Composite Reliability

Source of Heterogeneity	Variables Involved	Empirical Evidence from Data	Impact on Reliability
Hierarchical Role	Q6_hierarchy_level	Managers use ERP, BI, and automation systems; employees often report no AI or basic generative tools.	Non-uniform usage patterns
Technological Exposure	Q14_ai_tech_used	Coexistence of "No AI Technology Used" and advanced multi-AI tool stacks	Low inter-item correlation
Career Stage	Q7_years_company, Q8_years_position	Short tenure linked to limited AI exposure; longer tenure linked to selective adoption	Fragmented behavioral patterns
Decision Logic	Q18_ai_decision_main_factor, Q19_ai_decision_after_cost	Adoption is driven alternately by cost, ease, or scalability	Multiple adoption rationales
Employment Outlook	Q35_ai_new_vs_old_jobs	Coexistence of job creation and job elimination expectations	Mixed cognitive framing
Sectoral Tasks	Production vs. marketing vs. admin tools	AI applied to unrelated task domains	Multidimensional construct

Source : Elaborated by authors

Heterogeneity arises from differences in hierarchical roles, technological exposure, career stage, decision logic, employment outlook, and sectoral tasks. The relatively low composite reliability observed for the AI_Usage construct reflects the empirical heterogeneity of AI adoption rather than a measurement flaw. As evidenced by qualitative and demographic variables (Q6, Q7, Q8, Q14, Q18, Q19, Q35), AI usage among women in the Algerian agrifood industry is highly uneven, task-specific, and context-dependent. Respondents range from complete non-users ("No AI Technology Used") to advanced multi-tool users (e.g., ChatGPT, DeepSeek, Copilot, Firefly, BI-ERP, intelligent production systems). This dispersion violates the assumption of homogeneity required for high internal consistency in reflective constructs. Furthermore, AI usage varies systematically across hierarchical levels, tenure, and decision rationales. Managers tend to engage with AI strategically (ERP, BI, automation systems), while employees predominantly report either no usage or limited interaction with generative AI tools such as ChatGPT. Decision drivers such as cost, ease of implementation, and scalability further fragment AI usage patterns, reinforcing the construct's multidimensionality. In such conditions,

lower composite reliability is expected and does not invalidate the structural model, particularly in exploratory PLS-SEM contexts.

Consistent with PLS-SEM methodology, constructs with theoretical relevance and adequate convergent validity ($AVE > 0.50$) may be retained even when internal consistency is modest, especially when the construct captures emerging, evolving, or behaviorally diverse phenomena such as AI adoption in developing economies.

The implications of these findings are discussed in the following section, with particular attention to technology acceptance theory, AI literacy, and career adaptability among women in emerging economies.

4-Discussion:

This study provides an integrated understanding of AI awareness and adoption among women in the Algerian agrifood sector, showing how cognitive, behavioral, and contextual factors interact to shape engagement with AI technologies. Overall, the findings indicate that AI awareness, task-level integration, and familiarity remain low, suggesting that many respondents have not yet fully incorporated AI into their professional routines. These results align with prior studies emphasizing that foundational AI literacy may facilitate engagement with AI systems, though in this study, direct structural effects of familiarity were minimal (Long & Magerko, 2020).

Although respondents express willingness to reskill and adapt, this intention does not always translate into practical exposure, underscoring that cognitive readiness alone is insufficient without organizational support and enabling conditions (Nguyen, Nguyen, & Bui, 2023).

The results indicate that AI awareness among women in this context is shaped primarily by attitudinal and behavioral factors rather than demographic characteristics. Perceptions of usefulness, trust, and readiness to engage with AI matter more than age, tenure, or occupational category. This aligns with the Technology Acceptance Model (TAM), which holds that perceived usefulness and ease of use are primary drivers of technology adoption (Davis, 1989). Individuals who perceive AI as beneficial report greater readiness and trust in integrating it into work tasks, whereas women who see less value tend to remain skeptical or hesitant.

Role-based differences further reinforce this pattern: managers tend to evaluate AI strategically, emphasizing organizational performance and operational gains, whereas employees prioritize adaptability, skill development, and a learning orientation. This aligns with evidence from extended UTAUT models on self-efficacy and behavioral intention (Venkatesh, Thong, & Xu, 2012).

A notable insight from the study is the heterogeneity of AI use. Respondents range from complete non-users to advanced multi-tool users, indicating that adoption is highly contextual and task-specific. This diversity in usage patterns confirms prior calls to account for behavioral heterogeneity and contextual contingencies in technology acceptance research (Holone, 2021). Facilitating conditions, prior exposure, and organizational support shape adoption: respondents with greater access to AI infrastructure perceive it as more straightforward to use and more beneficial, whereas those with limited exposure report higher effort and lower perceived utility, consistent with UTAUT explanations of technology adoption variance (Venkatesh et al., 2012). Structural analysis confirms that AI usage is the primary determinant of awareness, while perceived cost savings are a secondary but meaningful factor. Recognizing tangible economic benefits, such as cost reductions, increases awareness by highlighting AI's utility. Conversely,

the perception that AI may reduce jobs exerts a modest constraining effect on awareness, suggesting that concerns about automation slightly influence engagement.

Practical experience with AI has a greater impact on awareness than theoretical familiarity, indicating that hands-on exposure is critical for effective adoption. In this study, the relatively low familiarity with AI among respondents reinforces the idea that underdeveloped digital skills may limit perceived utility and reduce motivational drivers, such as performance and effort expectancy (Long & Magerko, 2020).

The differentiated perceptions between managers and employees illustrate the moderating effects of organizational role and experience. Managers evaluate AI with a focus on strategic and operational outcomes, whereas employees emphasize adaptability and personal skill development. This distinction supports UTAUT's consideration of moderators such as social influence and facilitating conditions: leaders provide resources and normative guidance that shape others' adoption. At the same time, frontline employees rely more on personal confidence and perceived ease of use (Venkatesh et al., 2012). These results indicate that both structural and personal factors jointly influence technology engagement.

Overall, the structural model confirms that AI awareness among women in the Algerian agrifood sector is structured predominantly by experiential and attitudinal dimensions, practical usage, and perceived economic value. Job insecurity functions as a modest constraining factor. When interpreted alongside the exploratory MCA and PCA results, these findings demonstrate a coherent pattern in which attitudes, behaviors, and learning-oriented experiences outweigh demographic or purely organizational factors. Taken together, the results provide a robust empirical foundation for conceptualizing AI awareness as a socially and experientially grounded phenomenon in emerging-economy contexts.

4-1 Theoretical Implications

The study extends TAM and UTAUT frameworks by demonstrating that AI awareness in emerging economies is shaped not only by cognitive perceptions of usefulness and ease of use but also by attitudinal, behavioral, and emotional dimensions. Observed role-based differences highlight that organizational position moderates the relationship between perceived usefulness and adoption, confirming prior logic on hierarchical influence in technology acceptance (Venkatesh et al., 2012). Furthermore, the heterogeneity in AI usage supports calls to expand acceptance models to incorporate behavioral diversity and task-specific contingencies, particularly in sectors where adoption is uneven and evolving (Holone, 2021). These findings provide a nuanced understanding of AI adoption dynamics in developing contexts, emphasizing that cognitive readiness alone is insufficient to predict awareness or use.

4-2 Managerial Implications

Enhancing AI adoption requires a dual focus on technical competence and organizational support. Initiatives should strengthen AI literacy through targeted training, mentorship, and hands-on workshops, reinforcing that skill development underpins adoption (Long & Magerko, 2020). Highlighting tangible benefits, such as cost reduction and efficiency gains, can enhance perceived utility and motivate adoption, in line with UTAUT performance expectancy studies (Venkatesh et al., 2003). Facilitating conditions, including access to infrastructure, leadership guidance, and a supportive organizational culture, are critical to reduce perceived barriers and increase effort expectancy. Differentiated strategies should address both managerial and

employee needs: fostering strategic adoption and performance-oriented engagement at the managerial level, while promoting adaptability, skill development, and trust among frontline employees. Collectively, these measures support inclusive, effective, and context-sensitive AI integration in the agrifood sector and other emerging-economy settings.

In sum, these findings show how attitudinal, behavioral, and contextual factors shape AI awareness among women in the Algerian agrifood sector, highlighting key role-based differences. The following Conclusion draws together these insights and outlines avenues for future research.

Conclusion:

This study advances understanding of Artificial Intelligence awareness among women in the Algerian agrifood sector by positioning awareness as a foundational cognitive and attitudinal condition for technology adoption rather than a by-product of use. The findings show that AI awareness remains generally low to moderate, reflecting limited exposure to AI applications and weak organizational integration, despite an apparent willingness to learn and reskill. This gap suggests that constrained engagement is driven less by resistance or capability deficits than by restricted opportunities for hands-on interaction with AI technologies.

AI awareness emerges as a multidimensional construct shaped primarily by experiential engagement and evaluative orientations. Rather than being determined by age, tenure, or hierarchical position, awareness is organized around perceived usefulness, trust in engaging with AI systems, adaptability, willingness to reskill, and expectations of organizational value. These patterns indicate that AI awareness is not an individual attribute rooted in socio-demographic characteristics, but a socially and organizationally embedded process shaped by exposure, learning environments, and perceived relevance. In this sense, awareness functions as an upstream cognitive mechanism that conditions how women interpret, trust, and assign meaning to AI within their professional contexts.

Empirical results consistently identify hands-on AI use as the strongest determinant of awareness, clearly outweighing the influence of formal familiarity or system-level integration. Perceived cost reduction further reinforces awareness by linking AI to tangible economic benefits, particularly in resource-constrained organizational settings. At the same time, job displacement concerns exert a modest adverse effect, indicating that awareness simultaneously incorporates perceived opportunities and risks. This coexistence confirms that awareness does not follow a linear path toward acceptance, but reflects a nuanced cognitive state in which optimism and caution coexist.

Although organizational role does not fundamentally alter the level or structure of AI awareness, it shapes its interpretative framing. Managers tend to assess AI through a strategic lens focused on performance, efficiency, and employment risks, whereas employees emphasize learning opportunities, employability, and personal adaptability. These differences are meaningful but not polarizing, suggesting that hierarchical position influences emphasis rather than cognitive readiness itself.

Overall, the findings provide strong empirical support for the central role of experiential engagement in shaping AI awareness, partial support for the influence of organizational role, and explicit confirmation that awareness integrates both opportunity- and risk-based evaluations. By contrast, demographic and positional determinants receive no empirical

support. The study extends the TAM and UTAUT frameworks by explicitly conceptualizing AI awareness as a foundational cognitive construct that precedes perceived usefulness, trust, and behavioral intention. It also contributes to gender and technology research by showing that women's engagement with AI is shaped less by who they are within organizations and more by the nature and quality of experiential opportunities available to them.

From a practical perspective, the results position AI awareness as a critical lever for inclusive and sustainable digital transformation. Enhancing women's participation in AI-driven change requires more than access, policy commitments, or generic training. It calls for structured opportunities for hands-on engagement, role-sensitive learning pathways, and transparent communication of AI's economic and career implications. Without such conditions, expressed willingness to adapt risks remains symbolic rather than transformative.

Despite its contributions, the study is limited by its cross-sectional design, reliance on self-reported perceptions, and sector-specific focus, which constrain causal inference and generalizability. Future research would benefit from longitudinal, mixed-method, and multi-sectoral approaches, as well as comparative and intersectional designs, to examine how AI awareness translates into sustained adoption, career trajectories, and organizational outcomes. Ultimately, fostering AI awareness among women represents not only a prerequisite for equitable technology adoption but a strategic pathway toward more resilient, inclusive, and human-centered digital transformation in emerging digital economies.

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