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Digital Transformation in the Poultry Industry: Assessing Adoption Through the UTAUT Model and Managerial Profiles

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Keywords
Digitalization; UTAUT model; Poultry; Togo; Structure Equation Modeling (SEM)

Abstract

This study investigates the factors influencing the adoption and effective use of digital technologies in the poultry industry in Togo's Kara region. Using the UTAUT framework and a logit model, the study aimed to assess how perceptions of usefulness, ease of use, and managerial characteristics affect technology uptake. A purposive sample of 80 participants involved in breeding, retailing, slaughtering, feed supply, and poultry sales was surveyed. Data analysis was conducted using Smart PLS 4 for structural equation modeling and STATA 17 for logistic regression. Results show strong indicator reliability (outer loadings > 0.7), robust composite reliability (0.865–0.992), and acceptable convergent validity (AVE values > 0.5). Key findings reveal that performance expectancy and effort expectancy significantly influence behavioral intention and actual usage, emphasizing the importance of perceived productivity benefits and ease of use. In contrast, facilitating conditions, digital flexibility, and social influence were not significant. The socio-demographic analysis indicates that younger and male managers are more likely to adopt digital technologies, while marital status and cooperative membership showed no significant effects. These insights provide practical benefits by informing policy recommendations aimed at improving digital infrastructure, enhancing training programs, and designing targeted interventions that encourage broader digital adoption in Togo's poultry sector.

1. Introduction

The integration of digital technologies into agriculture has revolutionized the sector globally, driving efficiency, productivity, and sustainability through the use of information Internet of Things (IoT), Artificial intelligence (AI), precision agriculture, and connected sensors (Banik & Narendra, 2024; Zhang et al., 2024). Across the world, digital tools have enabled farmers and agribusinesses, and these advancements have been particularly transformative in addressing challenges such as climate change, resource management, and food security, making digitalization a cornerstone of agricultural development in the 21st century (Ashokkumar & Naik, 2021; Prahalathan et al., 2021).

In West Africa, where agriculture is a critical component of economic development and food security, digitalization is increasingly recognized as a catalyst for growth. Digital platforms and tools, including precision farming, mobile-based advisory services, and e-commerce channels, have significantly improved productivity and market integration (Abiri et al., 2023; Degila et al., 2023). For the poultry industry, a vital sub-sector of agriculture, digital solutions are proving invaluable in streamlining operations, facilitating better disease management, optimizing feed and production cycles, and enhancing supply chain transparency, ultimately boosting competitiveness and profitability (Zhang et al., 2024).

Despite the recognized potential of digitalization in agriculture, its adoption in the poultry sector in Togo remains limited and poorly documented (Degila et al., 2023). The sector continues to face structural barriers such as low initial productivity, weak infrastructure, limited internet connectivity, and persistent impacts of climate change, all of which hinder the integration of digital tools (Sekabira et al., 2023). Although the COVID-19 pandemic prompted some poultry enterprises to experiment with digital technologies to maintain operations, these instances were isolated and lacked strategic support (Sekabira et al., 2023). Government programs such as the Agricultural Productivity Program in West Africa-Togo (PPAAO) and the Agriculture Development Support Project in Togo (PADAT) have attempted to promote technological adoption in agriculture more broadly. However, these efforts have not been sufficiently targeted toward the poultry industry, resulting in uneven uptake and limited performance improvements. Moreover, the decentralization of agricultural governance and the recent, rapid growth of the poultry sector have led to significant data gaps, particularly concerning the determinants of digital adoption.

Existing literature underscores the transformative impact of digitalization on agricultural productivity and business performance (Kirillova et al., 2021; Kolmykova et al., 2021). Kolmykova et al., (2021) emphasized the importance of technological innovation in driving economic growth. While these benefits are well acknowledged, the determinants of digital adoption, particularly the role of individual and organizational factors (Dawane et al., 2025; Khidir et al., 2022), remain underexplored in the context of poultry farming in Togo. In particular, little is known about how managerial characteristics such as age, education, experience, and digital literacy influence technology acceptance in this sector.

Many challenges in adopting digital technology still exist in West African countries. Overcoming barriers to digital adoption in the poultry industry, particularly in Togo, requires a deeper understanding of these influencing factors. The lack of adequate infrastructure, including poor internet connectivity and unreliable electricity, impedes technology access and integration (Gbadebo, 2024; Oyenuga & Omale, 2024). This challenge is compounded by limited digital literacy, particularly among older populations and economically disadvantaged groups, who often lack the skills needed to engage with digital platforms effectively (Oteng et al., 2024). Furthermore, financial constraints significantly restrict access to technological devices, especially in rural areas where resources are scarce (Oyenuga & Omale, 2024; Wang, 2024). These interconnected barriers highlight the need to evaluate the effectiveness of digital technology adoption in addressing these challenges.

This paper aims to assess the factors influencing the adoption of digital technologies in Togo's poultry industries and the influence of managerial profiles on the adoption behavior. To achieve this, the Unified Theory of Acceptance and Use of Technology (UTAUT) model is applied as a theoretical framework, enabling a structured analysis of the behavioral and contextual variables that affect digital adoption. Additionally, the analysis of the managerial profile characteristics on the adoption behavior through the logit model make this study provides a novel approach to understanding the interplay between human factors and technology uptake in the agricultural sector.

Theoretical framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive model that explains how individuals adopt and use technology. It identifies four primary constructs that influence behavioral intention and actual use: performance expectancy (the belief that using the technology will provide benefits in job performance), effort expectancy (the ease associated with the use of the technology), social influence (the degree to which individuals perceive that important others believe they should use the new system), and facilitating conditions (the extent to which an individual believes that an organizational and technical infrastructure exists to support the use of the system). Performance expectancy and effort expectancy are particularly influential in shaping users' behavioral intention, while facilitating conditions primarily influence actual usage (Nugroho et al., 2024). Social influence, including peer recommendations and cultural norms, can also drive adoption, especially in environments where digital transformation is emerging or being promoted collectively (Cheng, 2024).

The UTAUT model has been widely recognized for its robustness and predictive power in various sectors, including agriculture. It has been effectively used to examine technology adoption among farmers and agribusiness operators (James et al., 2023; Sharma et al., 2024; Shi et al., 2022) Its multidimensional nature makes it well-suited to exploring how individual perceptions and contextual factors influence digital adoption in Togo's poultry industry. By adding managerial profiles' influence on the adoption behavior, the current study aims to generate more nuanced insights into the adoption process.

2. Materials and Methods

2.1 Study Area

The Kara region, located 400 km north of Lomé along National Road No. 1 in northern Togo, derives its name from the Kara River that traverses the region from east to west. Geographically positioned between 9°20' and 10°05' North latitude and 0°55' and 1°25' East longitude, the region covers an area of 11,738 km², representing approximately 21% of the national territory. Kara is bordered to the south by the Central region, to the north by the Savanes region, to the west by Ghana, and to the east by Benin. The area features diverse natural landscapes, alternating between vast plains, valleys, and plateaus interspersed with rugged old massifs, creating a unique topography. With a population of 769,940 inhabitants, Kara is the fourth most populated of Togo's five administrative regions.

2.2 Data Collection

The study employed a purposive sampling approach, targeting key stakeholders within the poultry industry, including breeders, retailers, slaughterhouse operators, feed suppliers, and poultry sellers. This non-probabilistic method was chosen due to the lack of reliable population data on poultry industry actors in the study area and the recent growth of interest in poultry farming in the region. Consequently, the selected sample reflects the diversity of actors actively engaged in the poultry value chain. A total of 80 participants were surveyed. Data collection was conducted via Google Forms. This approach enabled efficient data gathering across geographically dispersed respondents while ensuring accessibility.

The survey focused on factors outlined in the UTAUT model, including Digital Enjoyment, Digital Tools Interactivity, Digital Flexibility, Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions and quality of the digital which are the independent variables along with the main mediating variables behavioral intentions to use digital technologies, and the dependent variable which is the use behavior; these variables were measured by a 5-point Likert scale. These constructs were adopted to reflect the realities of global digitalization in poultry enterprises. Additionally, the socio-economic and demographic factors of the participants were collected to assess their impact on digital technology adoption (Smartphones, Desktop computers, and laptops).

2.3 Data Analysis

For the first hypothesis, structural equation modeling (SEM) was performed alongside confirmatory factor analysis to validate the constructs of the UTAUT model and their influence on digital tool utilization. For the second hypothesis, the binary nature of the dependent variable (use or non-use of digital tools in poultry enterprises) necessitated the use of a binary logit regression model to identify socioeconomic and demographic factors impacting digital technology adoption. This methodological approach ensures a robust analysis of the factors influencing the adoption and utilization of digital technology in the poultry sector within the Kara region.

2.4 Specification of the logit model

The binary logit model is widely used for analyzing binary choices due to its simplicity and similarity to the probit model. Dichotomous choice models provide detailed insights into adoption patterns and their drivers. According to the threshold decision-making theory (Hill & Kau, 1973), adoption depends on whether a stimulus value surpasses a critical threshold. If it does, adoption occurs; otherwise, it does not. This study focuses on characterizing adoption probabilities and understanding the determinants of technology uptake, emphasizing how profitability and uncertainty influence decisions. The approach offers a structured understanding of farmers' adoption behavior. Typically, this type of association is represented as:

$$Y_i = \beta X_i + u_i \qquad (1)$$

Where Y is the binary value (1 if the manager adopted the digital technology, 0 otherwise), then:

$$Y_i = \begin{Bmatrix} 1, if\ X_i \geq X* \\ 0, if\ X_i \leq X_i \end{Bmatrix} \text{ for all I = 1, 2…., n}$$

At the threshold level, X* represents the cumulative impact of all independent variables (Xi). The probability of technology adoption (Y) is functionally associated with independent variables (X), as indicated by Equation (1); then:

$$\mathrm{P}(Y_i = 1) = \mathrm{F}(\beta' X) \qquad (2)$$

$$\mathrm{P}(Y_i = 0) = 1 - \mathrm{F}(\beta' X) \qquad (3)$$

The ith observation's observed response is denoted as Yi, while Xi denotes a set of independent variables associated with the ith probability of adoption (P) of the digital technology. The function F has the potential to take on a logistic, normal, or probabilistic shape.

Following previous studies (Greene, 2012; Karidjo et al., 2018; Pivoto et al., 2019), the logit model is used to estimate P as follows:

$$\mathrm{P}(\mathrm{Y} - 1) = \frac{e^{\beta' X}}{1+e^{\beta' X}} \qquad (4)$$

$$\mathrm{P}(\mathrm{Y} - 0) = 1 - \frac{e^{\beta' X}}{1+e^{\beta' X}} = \frac{e^{\beta' X}}{1+e^{\beta' X}} \qquad (5)$$

The probability model can be represented as a regression of the conditional expectation of Y on X:

$$E\left(\frac{Y}{X}\right) = 1[\mathrm{F}(\beta' X')] + 0[1 - \mathrm{F}(\beta' X')] = \mathrm{F}(\beta' X') \quad (6)$$

Being a nonlinear model, the parameters exhibit dissimilarities from the marginal effects of the independent variables. To determine the impact of individual independent variables on the likelihood of adoption, we differentiate Equation (6) concerning X_{ij}, as illustrated below.

$$\frac{\partial P_i}{\partial X_{ij}} = \left[\frac{\theta^{\beta' X}}{1-\theta^{\beta' X}}\right]\beta = \mathrm{F}(\beta' X)[1 - \mathrm{F}(\beta' X)]\beta \quad (7)$$

The methodology above effectively addresses concerns related to heteroskedasticity and constrains the conditional probability of the decision to adopt the technology within the range of zero (0) to one (1). Both the logit and probit models have been widely employed in empirical studies due to their user-friendliness (Anang, 2018; Chuchird et al., 2017).

The empirical logit model is specified as:

$$Z_i = log\frac{P_i}{1-P_i} = \alpha\beta X_i + \mathcal{E}_i \quad (8)$$

Where $log\frac{P_i}{1-P_i}$ = logarithm of the odds of farmers' decision on whether to adopt improved technology or not and X_i = sum effect of the explanatory variables.

The analytical probit model is specified as:

$$Y_i = \beta_0 + \sum_{i=1}^{n}\beta_i X_i + \mathcal{E}_i \quad (9)$$

Where, Y_i, the digital technology (1 if adopted, 0 otherwise), β_0 Is the intercept, β_i is a vector of parameter estimates; X_i vector of the explanatory variable, and $\mathcal{E}_i$ The random disturbance term.

The vector of explanatory variables Xi comprises variables related to socio-demographic characteristics such as the age of the manager (AG), the manager's gender (SG), the type of activity (TA), the level of education (NIA), membership in a cooperative or poultry association (APCA), the number of years of experience in the field (NAE), and the marital status of the poultry enterprise manager (SM). The equation to be estimated is therefore

Digital adoption $=\alpha+\beta 1i\mathrm{AG}i+\beta 2i\mathrm{SG}i+\beta 3i\mathrm{SMA}i+\beta 4i\mathrm{NIA}i+\beta 5i\mathrm{APCA}i+\beta 6i\mathrm{TA}i+\beta 7i\mathrm{NAE}i+\varepsilon i$ (10)

3. Results and Discussion

3.1 Assessment of the adoption of digital technology in poultry industries

Confirmatory factor analysis

The results presented in Table 1 demonstrate excellent construct validity. All outer loading values exceed the threshold of 0.7, indicating strong reliability. Cronbach's alpha values range from 0.804 to 0.987, surpassing the acceptable threshold of 0.7 and confirming high internal consistency. Composite reliability values (0.865 – 0.992) further support the robustness of the constructs, while AVE values (0.681 – 0.975) confirm adequate convergent validity, as all exceed the benchmark of 0.5. These findings collectively validate the reliability and validity of the constructs for further analysis, aligning with established criteria (Fornell & Larcker, 1981; Hair et al., 2010).

Table 1. The construct validity

Constructs	Cronbach's alpha	Loading	Reliability	(AVE)
Behavioral intention	0.987	0.98 – 0.99	0.992	0.975
Digital system enjoyment	0.960	0.88 – 0.95	0.969	0.863
Digital system interactivity	0.906	0.76 – 0.90	0.930	0.727
Effort Expectancy	0.951	0.77 – 0.964	0.963	0.841
Facilitation condition	0.857	0.76 – 0.90	0.903	0.699
Digital system flexibility	0.960	0.88 – 0.97	0.969	0.864
Performance expectancy	0.957	0.90 – 0.96	0.969	0.886
Digital system quality	0.837	0.79 – 0.92	0.901	0.752
Social influence	0.804	0.81 – 0.83	0.865	0.681
Use behavior	0.962	0.94 – 0.98	0.976	0.930

Source: Author's data analysis (2024)

The data in Table 2 presents the R^2 and adjusted R^2 values, demonstrating the explanatory power of the structural model. Behavioral intention, with R^2 of 0.812 (adjusted R^2 of 0.794), serves as the primary mediating variable, explaining a substantial portion of the variance in the model. Effort expectancy (R^2 = 0.725, adjusted R^2 = 0.717) and performance expectancy (R^2 = 0.573, adjusted R^2 = 0.562) act as additional mediating variables, reflecting their roles in connecting predictor variables to other constructs. As the dependent variable, use behavior has a high R^2 of 0.774 (adjusted R^2 = 0.768), indicating that a large proportion of its variance is explained by the predictors, primarily mediated by behavioral intention. These results align with Fornell & Larcker, (1981), highlighting that R^2 values above

0.67 indicate substantial explanatory power in structural equation modeling, validating the robustness of the proposed relationships in the model.

The results presented in Table 3 demonstrate good discriminant validity based on the Fornell-Larcker criterion. The diagonal values in bold represent the square root of the Average Variance Extracted (AVE) for each construct, and all these values are more significant than 0.5, confirming adequate convergent validity. Furthermore, each bold diagonal value is greater than the correlations with other constructs in the same row or column, indicating that each construct shares more variance with its items than with items of other constructs. This ensures that the constructs are distinct from one another, providing evidence of discriminant validity as per (Fornell & Larcker, 1981).

Path analysis

Figure 1 presents a visualization of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, used to evaluate the effectiveness of digital technology adoption. It depicts independent variables such as digital system enjoyment, interactivity, quality, flexibility, social influence, and facilitation conditions. Independent mediating variables depicted include effort expectancy and performance expectancy. Behavioral intention serves as the primary independent and mediating variable, connecting the dependent variable with all other variables.

Direct effect

The results of the direct effects (Table 4) of the UTAUT model reveal several significant relationships. The behavioral intention has a strong and significant positive impact on use behavior (Coef. = 0.646, p < 0.001), emphasizing its central role in predicting actual usage. Digital system enjoyment significantly influences effort expectancy (Coef. = 0.281, p = 0.048) but does not directly affect behavioral intention or performance expectancy, indicating its limited direct role. Conversely, digital system interactivity significantly impacts both effort expectancy (Coef. = 0.604, p < 0.001) and performance expectancy (Coef. = 0.735, p < 0.001), highlighting its importance in shaping users' perceptions of the digital system. Effort expectancy also significantly influences behavioral intention (Coef. = 0.335, p = 0.021), suggesting that perceptions of users' ease of use are critical in forming intentions. Additionally, the facilitation condition positively impacts use behavior (Coef. = 0.279, p = 0.004) but does not significantly influence behavioral intention. Performance expectancy has a significant positive effect on behavioral intention (Coef. = 0.332, p = 0.006), underscoring its predictive power in user adoption.

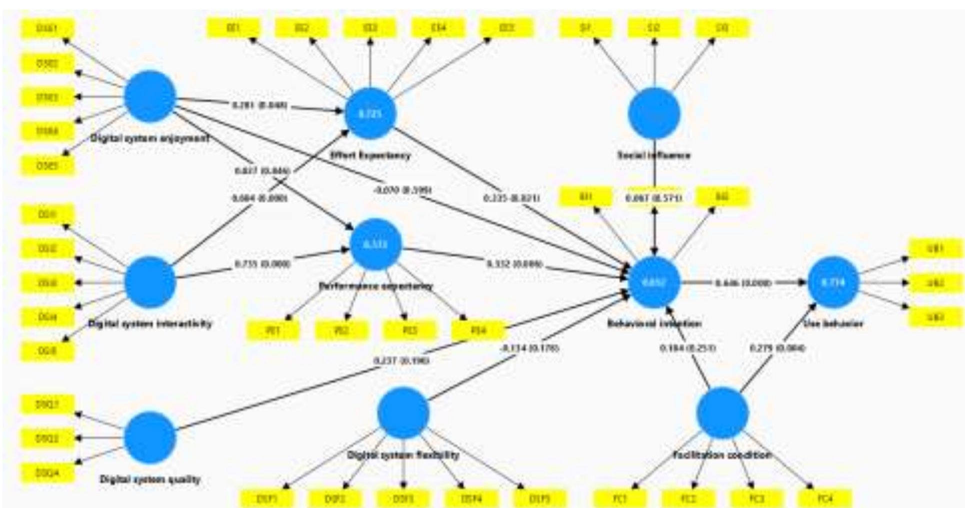

Figure 1. The Structural equation modeling of the UTAUT model
Source: Author's data analysis (2024)

Table 2. The R^2 value

Constructs	R^2	R^2 adjusted
Behavioral intention	0.812	0.794
Effort Expectancy	0.725	0.717
Performance expectancy	0.573	0.562
Use behavior	0.774	0.768

Source: Author's data analysis (2024)

Table 3. The Discriminant validity

Constructs	BI	DSE	DSI	EE	FC	DSF	PE	DSQ	SI	UB
Behavioral intention	0.988									
Digital system enjoyment	0.685	0.929								
Digital system interactivity	0.787	0.827	0.853							
Effort Expectancy	0.833	0.781	0.836	0.917						
Facilitation condition	0.774	0.665	0.712	0.783	0.836					
Digital system flexibility	0.589	0.620	0.682	0.690	0.662	0.930				
Performance expectancy	0.792	0.634	0.757	0.694	0.671	0.608	0.941			
Digital system quality	0.860	0.797	0.852	0.909	0.815	0.716	0.787	0.867		
Social influence	0.752	0.804	0.746	0.814	0.704	0.611	0.641	0.856	0.825	
Use behavior	0.862	0.808	0.815	0.811	0.779	0.571	0.809	0.811	0.700	0.965

Source: Author's data analysis (2024)

Table 4. Direct effects

Sous-hypothesis	Coef.	STDEV	T-value	P-values	Status
Behavioral intention -> Use behavior	0.646	0.091	7.085	0.000	Accepted
Digital system enjoyment -> Behavioral intention	-0.070	0.132	0.526	0.599	Rejected
Digital system enjoyment -> Effort Expectancy	0.281	0.143	1.974	0.048	Accepted
Digital system enjoyment -> Performance expectancy	0.027	0.137	0.194	0.846	Rejected
Digital system interactivity -> Effort Expectancy	0.604	0.125	4.828	0.000	Accepted
Digital system interactivity -> Performance expectancy	0.735	0.099	7.426	0.000	Accepted
Effort Expectancy -> Behavioral intention	0.335	0.145	2.317	0.021	Accepted
Facilitation condition -> Behavioral intention	0.184	0.160	1.149	0.251	Rejected
Facilitation condition -> Use behavior	0.279	0.097	2.860	0.004	Accepted
Digital system flexibility -> Behavioral intention	-0.134	0.099	1.347	0.178	Rejected
Performance expectancy -> Behavioral intention	0.332	0.121	2.755	0.006	Accepted
Digital system Quality -> Behavioral intention	0.237	0.183	1.294	0.196	Rejected
Social influence -> Behavioral intention	0.067	0.118	0.566	0.571	Rejected

Source: Author's data analysis (2024)

However, other variables, such as the digital system flexibility and quality, and social influence, show no significant direct effects on behavioral intention. These findings collectively highlight that while some constructs directly influence behavioral intention and use behavior, others may play a more nuanced or indirect role in the adoption.

Indirect effect

The results of the indirect effects (Table 5) of the UTAUT model provide insights into mediated relationships among the constructs. Digital system interactivity significantly influences behavioral intention (Coef. = 0.446, $p < 0.001$) and use behavior (Coef. = 0.288, $p = 0.001$), indicating its crucial role as a mediator in facilitating user adoption.

Effort expectancy indirectly impacts use behavior (Coef. = 0.216, $p = 0.024$), demonstrating that ease of use indirectly promotes digital system utilization. Performance expectancy also significantly mediates the relationship with use behavior (Coef. = 0.215, $p = 0.017$), reinforcing its importance in shaping users' adoption. However, other indirect paths, such as those involving digital system enjoyment, facilitation conditions, flexibility, quality, and social influence, were not statistically significant, as indicated by their high p-values.

These findings underscore the importance of specific constructs like interactivity and expectancy in driving indirect effects, while others might exert influence through alternative pathways.

3.2 Assessment of the socioeconomic factors that influence the adoption of digital technology

The model's log-likelihood is 24.157298, with higher values indicating a better fit. The Pseudo R^2 is 0.3488, suggesting that the model explains approximately 34.88% of the variance in the dependent variable. While this value is not particularly high, the significance of the model χ^2 ($P < 0.000$) indicates that the model has a certain level of explanatory power (Table 6).

The data in Table 6 reveals that the age of managers negatively impacts digital technology usage (coefficient = -1.78, $p = 0.028$), with old-aged managers less likely to adopt them. Conversely, gender shows a positive and nearly significant effect (coefficient = 2.22, $p = 0.043$), suggesting male managers are more inclined towards digitalization. Meanwhile, marital status (coefficient = 0.68, $p = 0.21$) and cooperative membership (coefficient = -1.15, $p = 0.21$)

do not significantly influence digital technology adoption. The model identifies age and gender as key factors impacting digital adoption among managers.

Table 5. Indirect effects

Sous-hypothesis	Coef.	STDEV	T-value	P-values	Status
Digital system enjoyment -> Behavioral intention	0.103	0.102	1.016	0.310	Rejected
Digital system enjoyment -> Use behavior	0.022	0.100	0.217	0.829	Rejected
Digital system interactivity -> Behavioral intention	0.446	0.103	4.319	0.000	Accepted
Digital system interactivity -> Use behavior	0.288	0.086	3.364	0.001	Accepted
Effort Expectancy -> Use behavior	0.216	0.096	2.264	0.024	Accepted
Facilitation condition -> Use behavior	0.119	0.104	1.137	0.255	Rejected
Flexibility of digital tool -> Use behavior	-0.086	0.068	1.270	0.204	Rejected
Performance expectancy -> Use behavior	0.215	0.089	2.398	0.017	Accepted
Digital system Quality -> Use behavior	0.153	0.112	1.365	0.172	Rejected
Social influence -> Use behavior	0.043	0.075	0.572	0.567	Rejected

Source: Author's data analysis (2024)

Table 6. The logit model estimation

Regression logistics			Number of observations = 80			
			$LR\chi^2(5)$ = 25.88			
			Prob > χ^2 = 0.0000			
The log-likelihood = -24.157298			Pseudo R^2 = 0.3488			
Use of Digital technology	Coef.	Std. err	z	P>|z|	[95% conf. interval]	
Age	-1.781	0.787	-2.26	0.024	0-3.324	-0.238
Gender	2.222	1.099	2.02	0.043	0.0670	4.377
Marital status	-0.418	1.031	-0.41	0.685	-2.440	1.603
Cooperative membership	-1.153	1.000	-1.15	0.249	-3.114	0.806
_cons	7.972	3.467	2.30	0.021	1.176	14.769

Source: Author's data analysis (2024)

Discussion

The analysis of the UTAUT model within the agricultural sector highlights significant findings regarding the factors influencing behavioral intention to adopt digital technologies. Performance expectancy directly and substantially impacts behavioral intention, confirming that businesses are more likely to adopt digital technologies when they anticipate performance gains. These findings align with the studies of (Indrayanto et al., 2024; Shi et al., 2022), which demonstrates that perceived improvements in productivity strongly motivate the adoption of digital technologies in agriculture. Similarly, effort expectancy positively influences behavioral intention, with perceptions of ease of use facilitating adoption. This finding resonates with the conclusions of (James et al., 2023), who observed that simplifying digital tools increases their adoption rates. However, facilitating conditions, digital flexibility, and social influence do not exhibit significant effects on behavioral intention within this model. This finding diverges from other studies (Buchdadi et al., 2024; James et al., 2023), which suggests that these factors play a significant role. Finally, behavioral intention emerges as a key predictor of actual usage, corroborating the results of Hong, (2022). This emphasizes that intention is a critical lever for transitioning to the practical use of digital technologies.

Regarding the indirect effects, performance expectancy and effort expectancy significantly influence actual usage through behavioral intention. These findings confirm that businesses perceiving benefits in terms of performance gains or low effort requirements are more likely to adopt digital technologies effectively. This observation aligns with the conclusions of (Sharma et al., 2024; Sihombing et al., 2024), which highlights the mediating role of behavioral intention in translating perceived benefits into actual adoption. However, facilitating conditions, digital flexibility, and social influence do not exhibit significant indirect effects within this model. This suggests that their role in the adoption process is limited when mediated by behavioral intention. These findings are consistent with the work of (Geng et al., 2024; M. N. Ismail, 2024), who observed that while these factors may exert influence in other contexts, they do not act as primary drivers of effective technology usage in the agricultural sector. These results underscore the critical importance of prioritizing perceptions of performance benefits and ease of use to foster adoption. Simultaneously, they highlight the need to explore specific contextual factors that may enrich the understanding and application of the UTAUT model across varying agricultural settings, allowing for more tailored and effective strategies to promote digital transformation.

The analysis of socio-economic and demographic factors influencing the adoption of digital technologies in agricultural enterprises highlights several key findings. Age and gender of the managers emerge as significant determinants, whereas marital status and cooperative membership show negligible effects. Age has a significantly negative impact on digital adoption, indicating that older managers are less inclined to integrate digital tools, possibly due to a lack of familiarity or perceived relevance, as supported by the findings (Fróna & Szenderák, 2024). Conversely, gender exerts a positive influence, with male managers being more likely to adopt digital technologies. This aligns with (Abdulai et al., 2023), who found that men often have greater access to resources and networks facilitating technological adoption. Meanwhile, marital status has no significant effect, corroborating (Ali, 2012) conclusions that family dynamics do not substantially affect technology use. Finally, cooperative membership shows a negative but non-significant effect, potentially reflecting internal barriers within these groups that limit digital engagement, as suggested by (Zelisko et al., 2024). These findings underscore the importance of age and gender while calling for further research into other variables such as education and resource access.

4. Conclusion and Recommendations

The study of digital transformation in the poultry industry using the UTAUT model and managerial profiles reveals that performance expectancy and effort expectancy are the primary drivers of behavioral intention and the actual usage of digital technologies. Anticipated performance improvements and ease of use significantly encourage adoption, underscoring their pivotal role. Conversely, facilitating conditions, digital flexibility, and social influence show negligible influence, suggesting that these factors are less critical in this specific context. The demographic analysis further highlights the significant impact of age and gender, with older managers demonstrating reluctance and male managers showing a higher propensity to adopt digital tools. These findings emphasize the importance of adopting strategies to sector-specific conditions, providing insights into how adoption dynamics are shaped within the agricultural domain. The study suggests that government policies and initiatives should focus on addressing the non-significant factors of the UTAUT model in this context, such as enhancing digital infrastructure and accessibility and fostering social influence through awareness campaigns. These efforts could bridge critical gaps and make digital transformation more inclusive and effective. Additionally, future research should explore the influence of the factors intrinsic to the use of digital technology on the technical and economic performance of the poultry industry. This approach, emphasizing actionable policies and theoretical advancements, can facilitate the widespread and sustainable adoption of digital technologies in agriculture, ultimately fostering industry growth and encouraging innovation.

Future research could explore cross-country comparisons to assess how regional differences influence digital adoption in the poultry sector across West Africa. Longitudinal studies are also needed to evaluate the long-term impacts of digital technology on business performance and operational sustainability. Additionally, further investigation into the role of digital literacy and targeted capacity-building programs would help determine their effectiveness in enhancing adoption rates among various actors in the poultry value chain. Agriculture extension service should focus on motivating farmers to:

Use mobile apps for tracking inventory, feed schedules, and health monitoring.
Attend local digital training workshops and farmer field schools.
Join WhatsApp or Telegram groups for poultry industry updates and peer support.
Start with simple tools like digital weighing scales or QR code-based traceability tags.
Partner with agri-tech startups or NGOs offering subsidized digital tools or training.

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