frontiers | Frontiers in Sustainable Food Systems

TYPE Systematic Review
PUBLISHED 04 February 2026
DOI 10.3389/fsufs.2026.1723715

OPEN ACCESS

EDITED BY
Idowu Oladele,
Global Center on Adaptation, Netherlands

REVIEWED BY
M. Lisa Yeo,
University of California, Merced, United States
Johnpaul M.,
Central University of Kerala, India

*CORRESPONDENCE
Alcade C. Segnon
✉ alcadese@gmail.com

RECEIVED 13 October 2025
REVISED 14 January 2026
ACCEPTED 23 January 2026
PUBLISHED 04 February 2026

CITATION
Gouroubera MW, Gouthon M, Segnon AC, Dosso F, Togbévi QF, Moumouni-Moussa I and Zougmoré RB (2026) Understanding farmers' acceptance of digital technologies: a meta-analytic structural equation modeling approach based on the technology acceptance model.
Front. Sustain. Food Syst. 10:1723715.
doi: 10.3389/fsufs.2026.1723715

Understanding farmers' acceptance of digital technologies: a meta-analytic structural equation modeling approach based on the technology acceptance model

Mori W. Gouroubera[1,2], Morrisson Gouthon[2], Alcade C. Segnon[1,3]*, Faridah Dosso[2], Quentin Fiacre Togbévi[3,4,5], Ismail Moumouni-Moussa[2] and Robert B. Zougmoré[1]

[1]International Center for Tropical Agriculture (CIAT), Dakar, Senegal, [2]Laboratory of Research on Innovation for Agricultural Development (LRIDA), Faculty of Agronomy, University of Parakou, Parakou, Benin, [3]Faculty of Agronomic Sciences, University of Abomey-Calavi, Cotonou, Benin, [4]Department of Water for Agriculture and Society, National Water Institute, University of Abomey-Calavi, Cotonou, Benin, [5]Laboratory of Hydraulics and Environmental Modeling (HydroModE-Lab), Faculty of Agronomy, University of Parakou, Parakou, Benin

Understanding how farmers accept and interact with digital technologies is crucial for transforming agriculture and improving smallholder livelihoods. Despite widespread use of the technology acceptance model (TAM) to understand farmers' adoption of digital technologies, findings remain inconsistent. We applied a two-stage meta-analytic structural equation modeling approach to synthesize 53 correlation matrices from 33 TAM studies involving 13,660 farmers across 17 countries. While the analysis confirms TAM's overall robustness in digital agricultural contexts, it also reveals unexpected findings. First, despite TAM's assumption that perceived ease of use (PEU) strongly predicts behavioral intention (BI), the meta-analytic results show that PEU has a weak and, in some models, non-significant effect on BI, challenging a core TAM hypothesis. In contrast, perceived usefulness (PU) consistently emerges as a strong determinant of attitude (AT) and remains central to farmers' acceptance of digital tools. The integration of external variables, particularly facilitating conditions (FC) and social influence (SI), meaningfully strengthens key TAM pathways, highlighting the importance of supportive environments and social dynamics. Unexpectedly, the type of digital technology does not moderate TAM relationships, indicating that farmers evaluate digital technologies more on perceived value than on technological complexity. Finally, despite generally positive behavioral intentions reported in primary studies, the meta-analysis identifies a persistent intention–use gap, with actual digital technology use remaining low. These findings underscore the need to tailor digital agriculture policies to farmers' perceptions, emphasizing practical benefits and supportive conditions to enhance adoption and contribute to the transformation of sustainable food systems.

KEYWORDS

digital agriculture, digital technology, meta-analysis, mobile phone, precision agriculture, structural equation modeling, technology adoption, technology acceptance model

1 Introduction

Digital technologies are transforming agriculture and food systems by addressing global challenges such as climate change, resource scarcity, and increasing productivity demands (Choruma et al., 2024; Prodhan et al., 2024; Shahriar et al., 2025; Dwivedi et al., 2022; Singh et al., 2023; Gouthon et al., 2024; Jumanne, 2024; Rosenstock et al., 2024). Numerous initiatives have been launched to enhance farmers' digital literacy and skills, yet the successful integration of these technologies ultimately depends on farmers' willingness to adopt innovations (Wang and Dong, 2023; Gao et al., 2024; Gouroubera et al., 2023b; Florea et al., 2024). Despite the significant potential of digital tools, adoption rates remain low, particularly among those with limited digital skills and knowledge (Gouroubera et al., 2023a, 2025; Rosenstock et al., 2024). Therefore, identifying the key factors influencing digital technology adoption is essential for scaling these innovations and improving farmers' livelihoods and resilience.

In the context of digital technologies, such as mobile decision-support apps, IoT sensors, remote-sensing dashboards, and e-market platforms, adoption hinges on design attributes that go beyond generic innovation characteristics. Digital tools are mediated by interface quality, data requirements, connectivity constraints, algorithmic transparency, and platform governance, which can systematically shape perceived usefulness, ease of use, trust, and risk perceptions (Bronson and Knezevic, 2016; Klerkx et al., 2019). The Technology Acceptance Model (TAM) is widely used framework for explaining farmers' acceptance of new technologies (Lima et al., 2018; Scherer et al., 2019; Mendes et al., 2024). According to TAM postulates, enhancing farmers' perceptions of the usefulness and ease of use of digital tools can promote their adoption. Over time, TAM has been extended to include additional variables such as social influence, self-efficacy, subjective norms, and facilitating conditions, which further elucidate the factors influencing technology acceptance in agricultural contexts (Schepers and Wetzels, 2007). Despite the widespread application of TAM, the literature on farmers' acceptance of digital technologies is fragmented, with inconsistent findings regarding the robustness of TAM models. While some studies confirm the hypothesized relationships within TAM, others report mixed results, leading to a lack of consensus on the factors influencing technology acceptance among farmers (Fox et al., 2021; Wu et al., 2022; Wang and Dong, 2023). These inconsistencies, coupled with significant variations across studies and agricultural contexts, highlight the need for a systematic synthesis of existing research to clarify these dynamics (Lima et al., 2018; Adewale Olusola, 2022).

While previous meta-analyses have largely examined technology acceptance across various occupational groups, there is a notable gap in research specifically addressing farmers' acceptance of digital technologies using the TAM framework (Molina-Maturano et al., 2021; Mazwane et al., 2023). As a result, policymakers and development practitioners lack consolidated evidence on which acceptance drivers are most influential for farmers and how interventions should be prioritized in agricultural settings. A sector-specific synthesis is therefore necessary to identify which pathways are robust, which are context-sensitive, and which may be amplified or weakened by agricultural realities such as extension support, community influence, and institutional arrangements. Thus, understanding the nuances of farmers' technology acceptance is crucial to explain the mechanisms that drive or hinder the adoption of digital solutions in agriculture (Herath, 2012; Farid et al., 2016; Sui and Gao, 2023).

In this meta-analysis, we employ a two-stage meta-analytic structural equation modeling (MASEM) approach to synthesize correlation matrices from studies on farmers' acceptance of digital technologies using the TAM framework. This method allows for a comprehensive analysis of TAM relationships, including model fit, moderation effects, and the impact of external variables. By focusing specifically on the agricultural sector, our research aims to generate insights that can inform policy and practice, thereby enhancing the adoption of digital technologies among farmers and supporting the ongoing transformation of agriculture and food systems.

2 Technology acceptance model in agriculture

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), is a widely used framework for explaining technology acceptance across various domains, including agriculture. TAM posits that perceived usefulness (PU) and perceived ease of use (PEU) are the primary determinants influencing users' attitude (AT) and behavioral intentions (BI) to adopt technology (USE). In agricultural contexts, TAM provides valuable insights into the factors driving digital technology adoption. Recent literature has expanded the traditional TAM framework by incorporating additional variables that may influence technology acceptance among farmers. For instance, Dwivedi et al. (2020) emphasize the importance of integrating constructs such as perceived enjoyment, compatibility, and social influence into the TAM framework to capture the nuances of user acceptance in specific contexts, including agriculture. These extensions recognize that technology acceptance is multifaceted, with social and contextual factors playing important roles alongside the core TAM constructs. Empirical studies have demonstrated the effectiveness of TAM in predicting digital technology acceptance among farmers. For example, Teo and Jarupunphol (2015) emphasize the widespread applicability of TAM in various fields, including agriculture, where understanding user acceptance is critical for the successful implementation of digital technologies. Similarly, Wang et al. (2022) extend the TAM to include motivational factors specific to agricultural contexts. Additionally, the integration of subjective norms and technology trust into the TAM framework significantly influences technology acceptance among farmers. Lee and Wan (2010) argue that incorporating these constructs can explain the factors that drive technology adoption, particularly in collectivist cultures where social influences are pronounced. Furthermore, integrating TAM with the Unified Theory of Acceptance and Use of Technology (UTAUT) offers a more comprehensive framework for examining farmers' acceptance of digital technologies. Venkatesh et al. (2016) proposed that UTAUT's constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—can be effectively combined with TAM to provide a more holistic understanding of technology acceptance in agricultural settings.

Various adaptations of TAM have been developed to incorporate context-specific variables (Taylor and Todd, 1995). Figure 1 illustrates the four models (M1, M2, M3, and M4) evaluated in this study, which differ in their inclusion of external variables. M1 represents the core

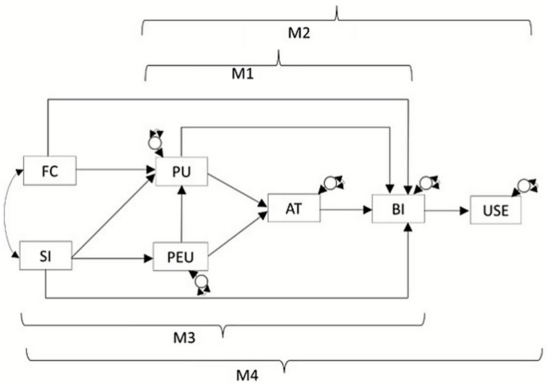

FIGURE 1
M1–4 represent the diverse models of farmers' digital technology acceptance.

TAM structure, focusing on behavioral intention (BI) as the main outcome, with perceived usefulness (PU), perceived ease of use (PEU), and attitude (AT) as predictors. M2 extends this framework by including actual technology use (USE), thereby addressing the often-overlooked gap between intention and actual use—an issue particularly pertinent in agricultural contexts where farmers may intend to adopt technology but encounter barriers to implementation. M3 and M4 further expand the models by incorporating external variables such as social influence and facilitating conditions, which serve as predictors of PU, PEU, and BI and are known to impact technology acceptance in various sectors (Tarhini et al., 2014; Santini et al., 2019).

3 Research questions

This meta-analysis synthesizes empirical evidence on farmers' adoption of digital technologies using the Technology Acceptance Model (TAM) as an analytical framework. Rather than re-validating TAM per se, the study aims to identify agriculture-specific adoption pathways and contextual conditions that shape farmers' digital technology use, with direct implications for extension, policy, and scaling strategies. The study addresses the following interrelated research questions (RQs):

RQ1: Agriculture-specific adoption mechanisms.To what extent do the core TAM relationships (PU, PEU, AT, and BI) consistently explain farmers' adoption of digital technologies across diverse agricultural contexts, and which pathways emerge as most influential for adoption decisions in farming systems? (Examined using pooled correlation matrices and MASEM structural models M1 and M2).

RQ2: Role of technology and farming context.How do differences in the type and function of digital agricultural technologies moderate TAM relationships, and what does this reveal about context-sensitive adoption dynamics in agriculture? (Examined through moderator analyses within MASEM models M1 and M2).

RQ3: Implications for intervention design in agriculture.How do external factors, particularly facilitating conditions and social influence, shape farmers' perceptions, intentions, and adoption behavior, and what do these relationships imply for the design of extension services, institutional support, and policy interventions aimed at scaling digital agriculture? (Examined through extended TAM models incorporating external variables, M3 and M4).

4 Methods

4.1 Literature search

To identify relevant scholarly articles for this meta-analysis, we collected papers from two databases, Scopus and Web of Science (WoS). The search strategy employed the following Boolean search string: ("Technology Acceptance Model" OR TAM* OR "technology acceptance") AND (digital OR ICT OR IoT) AND (agricult* OR farmer*). This search yielded 306 articles from Scopus and 151 articles from the WoS, resulting in an aggregate of 457 publications. This collection included peer-reviewed journal articles and book chapters relevant to the study. In addition to conducting searches within academic databases, a supplementary hand search was conducted on Google Scholar using the search terms "technology acceptance model" AND "farmer." This search identified four additional papers that were not included in the previously mentioned databases, thereby enriching the dataset. Furthermore, targeted searches were conducted in specific academic journals known for their focus on technology and agriculture. The journals included: *Information Technology for Development*, *Technological Forecasting & Social Change*, *Computers and Electronics in Agriculture*, *Technology in Society, and Smart Agricultural Technology*. These targeted searches yielded five additional papers.

4.2 Screening and selection criteria

Figure 2 presents the results of the literature search and screening process, following PRISMA guidelines (Moher et al., 2009). We conducted the publication screening in two steps using the CADIMA platform. Initially, after removing 51 duplicate publications from the original pool of 451, we screened the remaining titles and abstracts based on the predefined inclusion and exclusion criteria (Table 1). This initial screening process led to the exclusion of 343 publications, leaving 72 studies that met the preliminary criteria. During the second screening, we implemented additional inclusion and exclusion criteria to ensure that only studies offering relevant information about the farmer sample, relevant constructs of the TAM, and quantitative findings were included. To qualify as having sufficient quantitative results, a study had to present correlations between either manifest or latent variables, a complete variance–covariance matrix, or regression coefficients along with their corresponding standard errors. This process resulted in the selection of 33 studies (21 TAM and 12 UTAUT studies), which reported 53 correlation matrices (see Supplementary material for the list of the 33 relevant papers).

4.3 Measure of association and data extraction

We extracted correlations among key variables as measures of association. In cases where studies reported standardized path coefficients without correlation matrices, we converted these

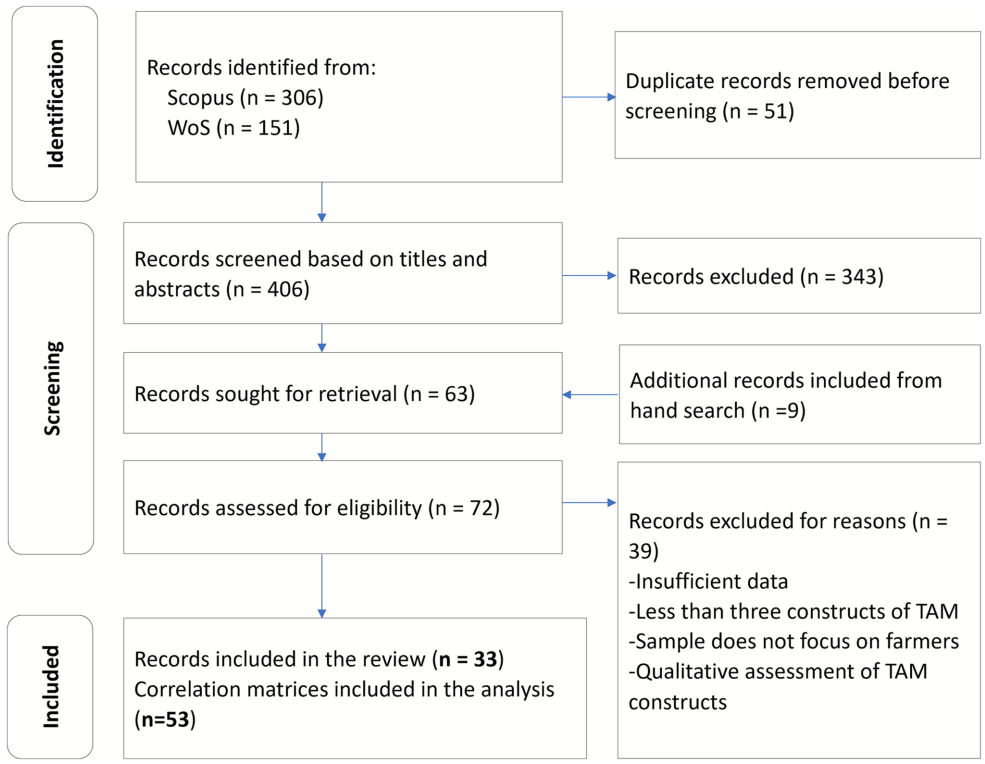

FIGURE 2
PRISMA diagram of the screening process.

coefficients (β) into correlations (r) using the formula $r = \beta + 0.05\lambda$. Here, λ is an indicator variable that is set to 1 when β is positive and 0 when β is negative (Peterson and Brown, 2005; Cohen, 2013; Chen and Chan, 2014). This conversion is crucial for maintaining consistency in our analysis across various studies. Moreover, when studies provided analyses for distinct groups, such as young versus older farmers or dairy farmers versus crop or vegetable farmers, we treated each group as a separate sample to ensure that our findings accurately reflected the diversity within the data. Our focus was primarily on the core TAM constructs: PU, PEU, AT, alongside relevant outcome variables like BI and USE. We also extracted correlations from external variables that could influence TAM constructs, including subjective norms, technology self-efficacy, and facilitating conditions (King and He, 2006; Marangunić and Granić, 2015). Despite the various external variables collected, we ultimately included only Facilitating Condition (FC) and Social Influence (SI) in our final analysis because of the limited reporting of correlations between TAM variables and self-efficacy or subjective norms. Notably, self-efficacy has often been operationalized as part of facilitating conditions, which can lead to confounding and multicollinearity issues (Czaja et al., 2006).

Some studies have employed UTAUT as a conceptual framework for examining farmers' digital acceptance (Keser et al., 2015; Venkatesh et al., 2016). We included studies in our analysis that presented adequate statistical information regarding the relationships among the relevant constructs. Although UTAUT labels certain variables differently, these constructs clearly correspond to those in TAM (Nistor and Heymann, 2010; Carraher Wolverton et al., 2020). For example, performance expectancy typically aligns with PU, while effort expectancy corresponds to PEU. The constructs of AT, BI, and USE are consistently labeled across both frameworks, reinforcing the robustness of these models in understanding technology acceptance.

To understand how study characteristics influence the relationships among constructs, we extracted several additional variables, including farmers' age, experience, economic development status (classified by income), and technology type. Technology types were grouped into (i) smart and IoT-based agricultural technologies and (ii) mobile-based digital technologies, following common classifications in digital agriculture research. Smart and IoT-based technologies include tools that rely on sensors, connectivity, and data analytics to support farm decision-making, such as precision agriculture systems, smart irrigation and fertilization platforms, IoT-enabled farm monitoring, and IoT-based agricultural e-commerce platforms that connect farmers to digital marketplaces for inputs and outputs through sensor- or platform-integrated systems. Mobile-based technologies refer to simpler, user-facing digital tools primarily delivered through mobile phones, such as agricultural mobile applications, SMS-based advisory services, mobile weather alerts, and mobile market information systems commonly used by smallholder farmers in low- and middle-income countries. We also considered some variables: the sample size, year of the study, and country. Among these variables, only technology type presents sufficient data for the moderation analysis.

4.4 Statistical analysis

4.4.1 Correlation-based MASEM

To synthesize the extracted correlation matrices related to TAM, we employed correlation-based MASEM using the Two-Stage

TABLE 1 Inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Study context	Studies specifically examining farmers' acceptance of digital technologies	Studies not focused on farmers or not examining digital technology acceptance.
Study design	Studies that quantitatively assessed the relationships among the constructs of the TAM or UTAUT using a structural equation modeling approach and reported at least one core TAM construct (PU, PEU, attitude, behavioral intention, or use) or its UTAUT equivalent (performance expectancy, effort expectancy).	Conceptual papers, literature reviews, and qualitative studies
Language of reporting	Studies providing relevant information, such as sample characteristics and results, in English or French	Studies reported in languages other than English or French, or lacking relevant data for analysis
Peer-reviewed status	Only peer-reviewed articles that ensure the quality and reliability of findings.	Non-peer-reviewed articles, conference proceedings, or unpublished theses without sufficient validation

Structural Equation Modeling (TSSEM) approach (Cheung and Chan, 2005; Cheung and Cheung, 2016). In the first stage, we combined the correlation matrices, typically using a random-effects model (Cheung, 2014). The second stage involved utilizing the generated correlation matrix to establish the proposed structural equation models. Unlike one-stage MASEM, which pools correlations separately, our method of pooling entire correlation matrices through multi-group modeling accounts for the nesting of correlations. This approach yields less biased estimates compared to univariate methods (Cheung and Chan, 2005; Jak, 2015). A significant advantage of this two-stage approach is its ability to apply a random-effects model during the pooling of correlation matrices, which enhances the accuracy of variable relationships and mitigates conflicting results across studies (Cheung and Cheung, 2016).

4.4.2 Model fit

The validity of the models was assessed through multiple chi-squared tests. To assess model fit, we checked several fit indices, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The fit of structural equation models was evaluated based on established guidelines for acceptable model fit criteria: CFI ≥ 0.95, RMSEA ≤ 0.08, and SRMR ≤ 0.10 (Hu and Bentler, 1999).

4.4.3 Moderation analysis

To explore potential differences within the sample, we conducted moderation analyses incorporating two variables in M1 and M2. The analysis focused on technology specificity, categorized as 1 for smart and IoT technologies (e.g., IoT e-commerce, smart farming, precision agriculture technologies) and 0 for mobile-based technologies (e.g., mobile apps, SMS technology). Previous research has indicated variations in digital technology usage according to its type (Van Dijk, 2017). We employed an omnibus test for moderation, a multivariate test designed to assess the presence of moderation effects.

5 Results

5.1 Characteristics of included TAM studies

Tables 2, 3 provide a summary of the $n = 33$ relevant studies with 53 correlation matrices, involving 13,660 farmers across 17 countries. There was a predominance of studies conducted in Germany (20.8%), followed by China (18.9%), Ethiopia (9.4%), and Mexico (9.4%). The study methods indicate a strong focus on latent variables (about 96% of studies). About 83% of the studies reported model fit evaluation statistics, among which 93.2% reported acceptable and close model fits (Table 2). About half of the studies (49.1%) reported smart/IoT technologies, and the remaining half reported mobile-based technologies (50.9%). The temporal trends indicate an increase in research on farmers' digital acceptance since 2021. The average age of farmers is approximately 46 years, with female farmers constituting about 29.84% of the total samples (Table 3) 0.11.24% of farmers have no formal education, while nearly 40% possess low or no education, which could hinder their ability to understand and utilize new technologies effectively. Conversely, 66% of farmers have middle to high levels of education, indicating a potential for positive technology acceptance among more educated individuals.

5.2 Aggregation of TAM correlations

The first step of the MASEM analysis involves calculating the pooled correlation matrices for each model using random-effect modeling. Significant between-study variation in individual correlation coefficients was found in most cases, with exceptions for one correlation in M1, two in M3, and one in M4 (see Tables 4, 5). The Q-statistics were significant across all four models 1–4, indicating existence of heterogeneity. Moreover, the variance attributable to between-study effects was substantial, with I^2 values ranging from 0% to 96.1% across different paths in the models. According to Table 4, the highest correlation in M1 and M2 was observed between PU and USE ($r = 0.51$), while the lowest was between BI and PEU ($r = 0.13$). In M3 and M4 (Table 5), the strongest correlation was between BI and AT, while the weakest was between FC and PEU.

5.3 Meta-analytic structural equation modeling

Using the pooled correlation matrices (see Tables 4, 5), we formulated the two primary models of the TAM, specifically M1

10.3389/fsufs.2026.1723715

TABLE 2 Summary of the categorical variables of the studies.

Variables	Number of studies	% of study samples
Location		
Brazil	1	1.9
China	10	18.9
Ethiopia	5	9.4
Germany	11	20.8
Greece	1	1.9
India	1	3.8
Iran	2	3.8
Iraq	1	1.9
Italy	3	5.7
Mexico	5	9.4
Nepal	1	1.9
South Africa	3	5.7
United States	1	1.9
Sri Lanka	1	1.9
Thailand	2	3.8
Uganda	3	5.7
Vietnam	1	1.9
Representation of TAM variables		
Latent	51	96.2
Manifest	0	0
Latent and manifest	2	3.8
Model fit evaluation		
Yes	44	83
No	9	17
Quality of the model fit[a]		
Poor	0	0
Mediocre	3	6.8
Acceptable	8	86.4
Close	3	6.8
Type of technology		
Smart and IoT technologies	26	49.1
Mobile-based technologies	27	50.9
Publication year		
2005	1	1.9
2011	1	1.9
2017	2	3.8
2018	6	11.3
2019	1	1.9
2020	6	11.3
2021	18	34.0
2022	7	13.2
2023	5	9.4
2024	6	11.3

[a]Guideline used for model fit categorization (e.g., Scherer et al., 2019): Poor (RMSEA > 0.10, CFI < 0.85), mediocre (0.08 < RMSEA ≤ 0.10, 0.85 ≤ CFI < 0.90), acceptable (0.05 < RMSEA ≤ 0.08, 0.90 ≤ CFI < 0.95), and close (RMSEA ≤ 0.05, CFI ≥ 0.95).

and M2, to evaluate how well the TAM corresponds with the empirical data obtained from farmers, including both direct and indirect effects.

Model 1. The analysis demonstrates a good fit to the data in the M1, Chi^2 (1) = 2.834, $p = 0.092$, RMSEA = 0.012 [0; 0.028], SRMR = 0.0304, CFI = 0.9945, TLI = 0.9673, AIC = 0.8338, BIC = −6.6885 (Figure 3). The results indicated positive and statistically significant path coefficients for all established relationships. Figure 3 indicates the complete set of parameters in M1 and their 95% likelihood-based confidence intervals. The direct effect PU → BI and PEU → AT was weak but significant, respectively, $\beta = 0.15$, 95% CI = [0.02; 0.27] and $\beta = 0.15$, 95% CI = [0.02; 0.28]. A stronger and more significant association was obtained on the effect PEU → PU, $\beta = 0.43$, 95% CI = [0.30; 0.54].

Model 2. In M2 with the additional effects BI → USE and PEU → BI, the analysis indicates a good fit, Chi^2 (3) = 26.37, $p = 0$, RMSEA = 0.024 [0.016; 0.033], SRMR = 0.15, CFI = 0.9512, TLI = 0.8373, AIC = 20.37, BIC = −2.19 (Figure 4). However, the effect PEU → BI was negative and non-significant, $\beta = -0.06$, 95% CI = [−0.18; 0.06]. The direct effect AT → USE was positive and significant, $\beta = 0.32$, 95% CI = [0.25; 0.37]. We also notice an increase in the direct PU → BI effect, $\beta = 0.26$, 95% CI = [0.14; 0.36]. As in model 1, the weak effect was PEU → AT $\beta = 0.20$, 95% CI = [0.07; 0.33], and the stronger effect was on the effect PEU → PU, $\beta = 0.45$, 95% CI = [0.33; 0.57].

Overall, the findings in M1 and M2 respond to the research question (RQ1) by demonstrating that TAM, with its hypothesized direct effects, adequately explains farmers' adoption of digital technologies. The empirical establishment of these direct effects, specifically PEU → BI, PU → AT, PEU → AT, PU → BI, AT → BI, and BI → USE, supports the model's validity in explaining farmers' acceptance of digital technologies.

5.4 Moderation analysis

To address RQ2, we conducted a moderation analysis with M1 and M2. The moderation analysis included technology type, with Smart and IoT technologies coded as 1 and Mobile-based technologies coded as 0. 49% of the studies examined Smart and IoT technologies, while 51% focused on Mobile-based technologies. The omnibus tests of moderator effects show that technology type did not moderate digital technologies acceptance (Tables 6, 7).

5.5 Effects of external variables

To assess the influence of external variables, we extended M1 and M2 to include two commonly used UTAUT variables: FC and SI, which served as predictors of PU, PEU, and BI (see Figures 5, 6). M3 and M4

TABLE 3 Summary of the continuous variables of the studies.

Variables	Mean	SD	Min	Max	Number of studies
Sample size	257.73	158.18	22	727	33
Average age (years)	45.96	8.82	25	59.50	12
Proportion of female farmers	29.84%	22.09%	0.00%	100%	25
Farmers education					
None	11.24%	14.01%	0.20%	47.6%	13
Low	28.53%	18.51%	0.40%	76.8%	20
Middle	35.14%	20.79%	1.70%	75%	21
High	30.94%	26.75%	2.27%	91.40%	22
Reliability coefficients (Cronbach's α)					
FC	0.821	0.0344	0.742	0.866	18
SI	0.836	0.0643	0.733	0.970	26
PU	0.872	0.0628	0.620	0.960	37
PEU	0.852	0.0731	0.676	0.971	37
AT	0.867	0.0709	0.770	0.983	9
BI	0.866	0.0670	0.720	0.970	34
USE	0.873	0.1038	0.720	1.000	7

TABLE 4 Pooled correlation matrices under a random-effects model (TSSEM-Stage 1) for M1 and M2 from the meta-analysis.

TAM constructs	PU	PEU	AT	BI
PU	$k = 51$ ($n = 13,508$)			
PEU	$k = 51$($n = 13,285$)			
r	0.44***			
95% CI	[0.32, 0.57]			
τ^2	0.058**			
SE (τ^2)	0.021			
I^2	95.95%			
AT	$k = 14$ ($n = 4,688$)			
r	0.45***	0.35***		
95% CI	[0.34, 0.57]	[0.05, 0.21]		
τ^2	0.03*	0.01*		
SE (τ^2)	0.015	0.009		
I^2	93.1%	85.72%		
BI	$k = 49$ ($n = 12,358$)			
r	0.34***	0.13***	0.48***	
95% CI	[0.28, 0.40]	[0.34, 0.62]	[0.34, 0.62]	
τ^2	0.035***	0.05***	0.06*	
SE (τ^2)	0.008	0.01	0.02	
I^2	92.3%	93.7%	096.1%	
USE	$k = 20$ ($n = 5,068$)			
r	0.51***	0.48***	—	0.34***
95% CI	[0.23, 0.79]	[0.34, 0.62]	—	[0.28, 0.40]
τ^2	0.03	0.05*	—	0.01*
SE (τ^2)	0.04	0.02	—	0.005
I^2	95.8%	96.1%	—	79.5%

Random-effects model-based correlation matrices (k = number of study samples; n = sample). The correlation matrix above the "USE" line is that of M1; the entire correlation matrix is that of M2. r: aggregated correlation, τ^2: variance between correlation matrices (i.e., study samples), I^2: heterogeneity coefficient based on the Q statistic (Higgins et al., 2008). *$p < 0.01$, **$p < 0.05$, ***$p < 0.001$.

TABLE 5 Pooled correlation matrices under a random-effects model (TSSEM-Stage 1) for M3 and M4 from the meta-analysis.

TAM constructs	PU	PEU	AT	BI	FC	SI
PU	$k = 51$ ($n = 13{,}508$)					
PEU	$k = 51$($n = 13{,}285$)					
r	0.44***					
95% CI	[0.32, 0.57]					
τ^2	0.058**					
SE (τ^2)	0.021					
I^2	95.95%					
AT	$k = 14$ ($n = 4{,}688$)					
r	0.45***	0.35***				
95% CI	[0.34, 0.57]	[0.05, 0.21]				
τ^2	0.03*	0.01*				
SE (τ^2)	0.015	0.009				
I^2	93.1%	85.72%				
BI	$k = 49$ ($n = 12{,}358$)					
r	0.34***	0.13***	0.48***			
95% CI	[0.28, 0.40]	[0.34, 0.62]	[0.34, 0.62]			
τ^2	0.035***	0.05***	0.06*			
SE (τ^2)	0.008	0.01	0.02			
I^2	92.3%	93.7%	96.1%			
FC	$k = 28$ ($n = 6{,}338$)					
r	0.11	0.05	0.42***	0.24**		
95% CI	[−0.14, 0.36]	[−0.23, 0.35]	[0.34, 0.49]	[0.15, 0.33]		
τ^2	0.04	0.04	—	0.04***		
SE (τ^2)	0.04	0.04	—	0.014		
I^2	92.3%	91.7%	0%	93.4%		
SI	$k = 39$ ($n = 2{,}331$)					
r	0.37***	0.21***	0.37***	0.18***	0.36***	
95% CI	[0.23, 0.50]	[0.09, 0.33]	[0.24, 0.50]	[0.03, 0.11]	[0.29, 0.43]	
τ^2	0.03***	0.01***	0.006***	0.03***	—	
SE (τ^2)	0.01	0.01	0.008	0.01	—	
I^2	93%	76.3%	69.5%	91.8%	0%	
USE	$k = 20$ ($n = 5{,}068$)					
r	0.056	0.50***	—	0.34***	0.30***	—
95% CI	[0.06, −0.06]	[0.22, 0.7]	—	[0.28, 0.40]	[0.22, 0.37]	—
τ^2	0.003	0.04*	—	0.01*	0.01***	—
SE (τ^2)	0.007	0.04	—	0.004	0.008	—
I^2	47.7%	96.06%	—	78.5%	86.2%	—

Random-effects model-based correlation matrices (k = number of study samples; n = sample). The correlation matrix above the "USE" line is that of M3; the entire correlation matrix is that of M4. r: aggregated correlation, τ^2: variance between correlation matrices (i.e., study samples), I^2: heterogeneity coefficient based on the Q statistic (Higgins et al., 2008). *$p < 0.01$, **$p < 0.05$, ***$p < 0.001$.

demonstrated good model fit. Our findings showed that in both M3 and M4, neither FC nor social SI predicted PEU of use, but both influenced PU. Additionally, FC predicted BI only in M4. Moreover, the introduction of these external variables enhanced the path coefficients in TAM relationships across both models except for the effect PEU → BI.

6 Discussion

This MASEM study provides insights into the factors influencing farmers' acceptance of digital technologies. By synthesizing 53 correlation matrices from 33 empirical studies involving over 13,660

farmers, we elucidate the relationships among key TAM constructs, PU, PEU, AT, BI, and USE, in the agricultural context.

6.1 Model fit, TAM variables relationship, and generalizability

The findings show that the four models (M1-4) have good and similar fit using random effects models, supporting the validity of TAM models and their applicability to farmers' samples in digital acceptance studies. Cheung and Cheung (2016) as well as recent studies in other domains (Scherer et al., 2019) highlighted the effectiveness of synthesizing correlation matrices based on random effects models rather than fixed-effects models. Furthermore, findings confirm that both PU and PEU are significant predictors of farmers' attitudes toward digital technologies, consistent with existing literature on TAM (Calisir et al., 2009; Nasser Al-Suqri, 2014; Scherer et al., 2019). It is worth noticing that the effect PU → AT is stronger than the effect PEU → AT, showing that instrumental value and expected performance gains outweigh usability concerns for farmers. Farmers who perceive digital technologies as beneficial and easy to use are more likely to develop positive attitudes and intentions to adopt them. This indicates the importance of enhancing farmers' perceptions through targeted training and support programs that emphasize the practical benefits and usability of digital tools. For instance, initiatives that demonstrate how digital technologies can improve productivity or reduce costs may significantly influence acceptance rates (Effendy et al., 2021; Sulandjari et al., 2023). Unexpectedly, the moderation analysis shows that technology type, smart/IoT-based systems versus mobile-based technologies, does not significantly alter the strength or direction of TAM relationships. This challenges the common expectation that greater technical complexity would systematically depress PEU or elevate risk perceptions relative to simpler mobile tools, thereby reshaping adoption pathways. Instead, the pooled estimates suggest that farmers' cognitive processing of digital adoption decisions is functionally similar across modalities, with PU and PEU. This aligns with long-standing evidence that TAM's core perceptual mechanisms generalize across technologies and user segments (Venkatesh, 2000; Venkatesh and Zhang, 2010).

Moreover, the results indicate that external factors, including FC and SI, significantly impact technology acceptance among farmers (Kerr et al., 2018). These findings align with previous research highlighting the role of community engagement and cooperative structures in fostering a supportive environment for technology adoption. By participating in farmer groups or cooperatives, individuals can share experiences and resources, which can mitigate perceived risks associated with adopting new technologies (Mahaputra and Mahaputra, 2023). Therefore, enhancing community support networks may be a strategic approach to increase technology acceptance in agricultural settings, as community dynamics often play a pivotal role in shaping individual attitudes and intentions toward technology use (Agarwal and Prasad, 1999; Stocchi et al., 2019).

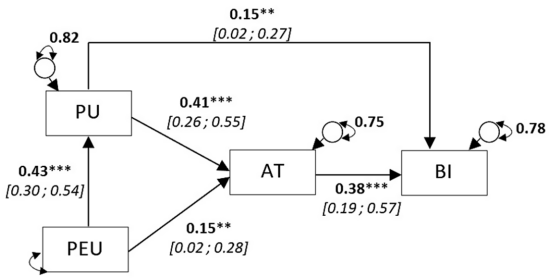

FIGURE 3
M1 core TAM variables.

6.2 Addressing inconsistencies and revealing the intention–behavior gap

Despite broad support for TAM relationships, this meta-analysis highlights inconsistencies across studies, particularly when external variables are introduced. While all core TAM paths are significant in baseline models with the core variables (M1 and M2), some relationships, such as PEU → AT, lose significance in extended models (M3 and M4). This demonstrates that once institutional and social constraints are accounted for, cognitive evaluations alone may no longer fully explain farmers' attitudes, echoing concerns raised in prior empirical work

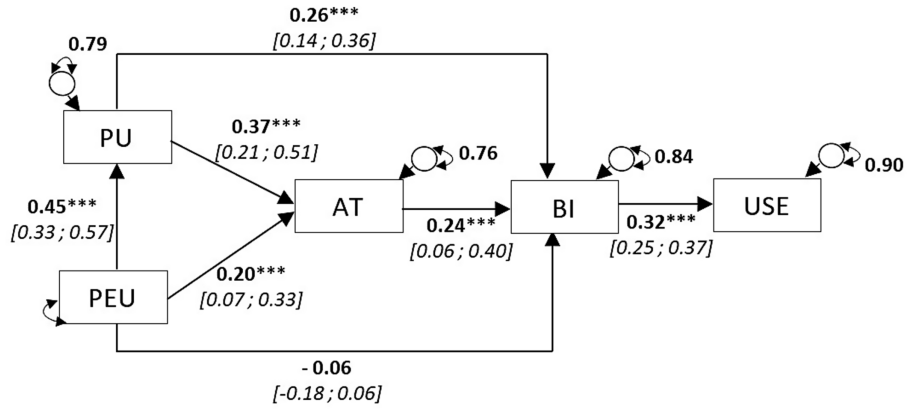

FIGURE 4
M2 core TAM variables including effect BI → USE and PEU → BI.

(McCormack et al., 2021; Dissanayake et al., 2022; Okai et al., 2024). The study also reveals an intention-behavior gap in agricultural digital adoption. Although many studies report positive intentions to adopt digital technologies, actual use remains low. In practice, farmers may recognize long-term benefits of digital tools but postpone or avoid adoption due to immediate costs, uncertainty, or competing livelihood priorities. In smallholder systems, where margins are thin and shocks are frequent, even minor implementation risks can outweigh anticipated gains (Sun et al., 2022; Wang and Dong, 2023). Furthermore, limited access to reliable internet, inadequate technical support, lack of complementary inputs, and weak extension follow-up often prevent intentions from translating into sustained use. These constraints highlight that adoption is not a single decision but a process requiring continuous reinforcement (Thi Hoa Sen et al., 2024; Mulungu et al., 2025; Vijayakumar et al., 2025). Therefore, future interventions should move beyond awareness-raising and intention formation toward implementation-oriented strategies, such as embedded extension support, trialability mechanisms, peer demonstration plots, and risk-sharing arrangements. Conceptually, this reveals the need to complement TAM with implementation and behavioral frameworks that account for structural constraints and adaptive decision-making under uncertainty. Doing so can provide a more realistic and policy-relevant understanding of how digital technologies diffuse within agricultural systems.

TABLE 6 Omnibus test of moderating effects.

Statistics	M1	M2
Moderator distribution (%)	49	49
Omnibus test	$\chi^2 = 2.82$	$\chi^2 = 5.52$
	$p = 0.727$	$p = 0.596$

TABLE 7 Individual moderating effects.

Paths	Technology type (smart and IoT / mobile-based technology)		
	Estimate (SD)	*z* value	*p*-value
M1			
PU → AT	0.028 (0.15)	0.18	0.85
PU → BI	−0.16 (0.12)	−1.31	0.18
PEU → PU	−0.04 (0.12)	−0.38	0.69
PEU → AT	−0.06 (0.13)	−0.47	0.63
AT → BI	0.26 (0.18)	1.43	0.15
M2			
PU → AT	0.007 (0.15)	0.04	0.96
PU → BI	−0.14 (0.12)	−1.09	0.27
PEU → PU	−0.06 (0.12)	−0.52	0.60
PEU → AT	−0.01 (0.13)	−0.12	0.90
PEU → BI	−0.05 (0.13)	−0.39	0.69
AT → BI	0.28 (0.18)	1.58	0.11
BI → USE	−0.11 (0.06)	−1.77	0.07

6.3 Limitations and future research directions

This meta-analytic review has some limitations worth noting. First, the meta-analysis was restricted by the limited availability of complete correlation matrices across primary studies for external variables, which allowed consistent synthesis only for facilitating conditions and social influence. Second, although we assessed whether technology type moderated TAM relationships, the available studies did not provide sufficient diversity in digital tools to capture meaningful differences between mobile-based and smart/IoT solutions. This limits the generalizability of the moderation findings. These limitations highlight several avenues for future research. More comprehensive reporting of correlation matrices in primary studies would allow more complete testing of TAM constructs, including effort expectancy, compatibility, and perceived risk. Future studies should also examine technology-specific adoption dynamics to better understand when and why different digital tools shape behavioral constructs differently. Research integrating longitudinal designs,

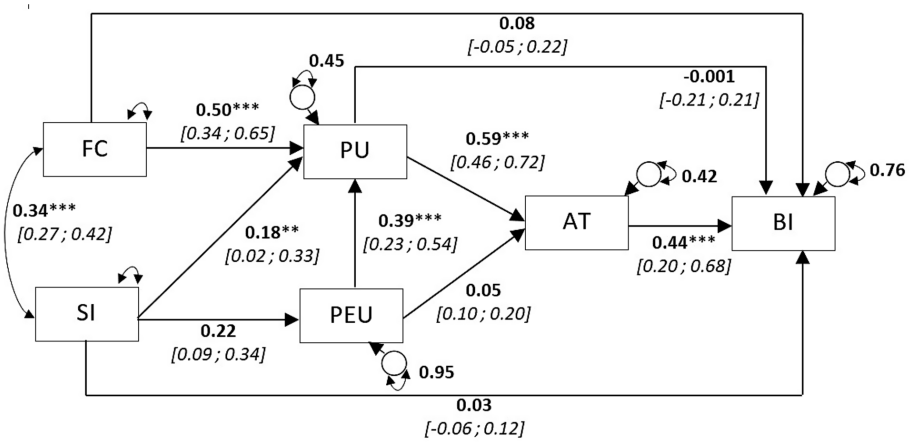

FIGURE 5
M3 extension of M1.

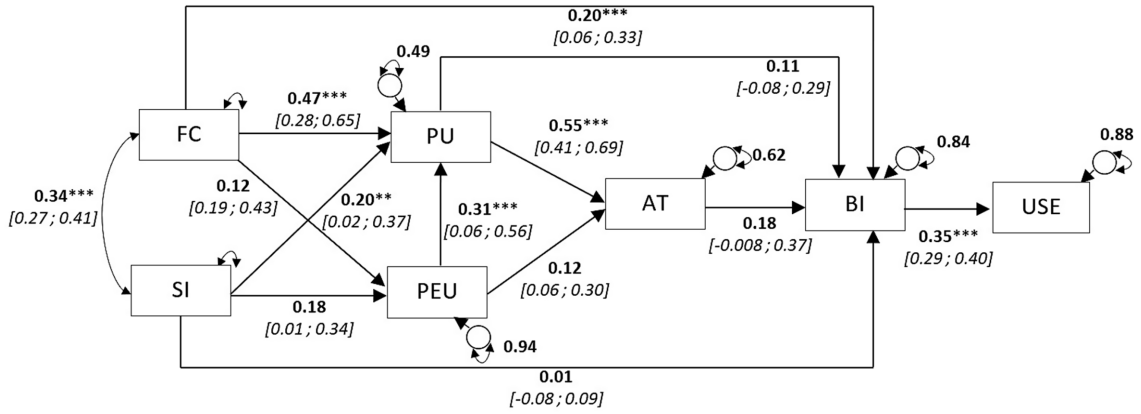

FIGURE 6
M4 extension of M2.

behavioral economic experiments, or mixed-methods approaches would help clarify the mechanisms underlying the intention–behavior gap. Finally, future work should explicitly model structural and institutional factors, such as digital infrastructure quality, access to complementary inputs, and the strength of extension and support systems, to better explain why positive intentions do not consistently translate into sustained digital tool use among farmers.

7 Conclusion

This meta-analysis advances understanding of farmers' acceptance of digital technologies using a two-stage MASEM of TAM. Across studies, perceived usefulness and perceived ease of use consistently emerge as primary drivers of attitudes and behavioral intentions. In parallel, facilitating conditions and social influence shape these core perceptions, indicating that adoption is embedded in farmers' operational and social environments rather than solely in individual evaluations. Notably, the analysis shows no significant differences in TAM relationships by technology type. Farmers judge tools on practical value and usability more than on technological category. At the same time, the study highlights an intention-behavior gap: positive intentions do not reliably translate into sustained use. This gap points to implementation frictions, learning costs, uncertainty about returns, thin margins, and intermittent support that require continuous reinforcement beyond initial training. Practically, policy and program design should pair user-centered training with stable infrastructure, on-farm technical assistance, follow-up extension, and access to complementary inputs. By focusing on these aspects of technology acceptance within agriculture, the study contributes to the academic discourse and offers practical implications for policymakers seeking to enhance digital literacy among farmers and ultimately transform agricultural practices through effective technology integration.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MWG: Data curation, Formal analysis, Conceptualization, Methodology, Visualization, Writing – review & editing, Writing – original draft, Investigation. MG: Writing – original draft, Formal analysis, Conceptualization, Investigation, Data curation, Writing – review & editing. AS: Resources, Writing – original draft, Visualization, Writing – review & editing, Conceptualization, Validation, Supervision. FD: Data curation, Conceptualization, Writing – original draft, Formal analysis, Writing – review & editing. QT: Visualization, Validation, Writing – original draft, Writing – review & editing, Formal analysis. IM-M: Visualization, Writing – original draft, Supervision, Validation, Writing – review & editing. RZ: Writing – original draft, Writing – review & editing, Validation, Funding acquisition, Supervision.

Funding

The author(s) declared that financial support was received for this work and/or its publication. The paper was developed with funding support from the Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) project, funded by a grant from the International Development Association (IDA) of the World Bank.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2026.1723715/full#supplementary-material

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