GIJEA
Greenation International Journal of Economics and Accounting
+62 81210467572 https://research.e-greenation.org/GIJEA greenation.info@gmail.com
GREENATION RESEARCH

DOI: https://doi.org/10.38035/gijea.v4i4.1287
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Received: 04 August 2026 | **Revised:** 20 October 2026 | **Accepted:** 30 October 2026

Determinants of Continued Use of Virtual Livestock Marketplaces: An Extended UTAUT2 Model of Farm Productivity and Business Sustainability among Ruminant Farmers in Jabodetabek

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Abstract: Inefficiencies and middleman price suppression in traditional livestock supply chains necessitate digital transformation in smallholder agriculture. This study analyzes the determinants of virtual livestock market continued use intention among existing smallholder ruminant farmers in Jabodetabek by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with Individual Factors (age and income) moderation, and evaluates its downstream impacts on farm productivity and sustainability. Survey data from 200 smallholders selected via quota sampling were analyzed using SEM-PLS. The empirical results indicate that behavioral intention is substantially explained (R^2 = 76.7%), with Hedonic Motivation emerging as the primary driver, followed by Effort Expectancy, Habit, Price Value, Social Influence, and Performance Expectancy. Facilitating Conditions and direct Individual Factors are non-significant due to peri-urban infrastructure saturation, although Individual Factors significantly moderate six UTAUT2 adoption pathways. Furthermore, behavioral intention strongly drives actual use behavior (0.715), which is positively associated with farm productivity (R^2 = 52.0%) and multidimensional sustainability (R^2 = 47.5%). These findings highlight that user-friendly, engaging, and community-validated digital platforms are vital to strengthening smallholder agribusiness resilience and biosecurity.

Keyword: UTAUT2, SEM-PLS, Virtual Livestock Market, Individual Factors Moderation, Ruminant Farmers, Farm Productivity, Agribusiness Sustainability.

INTRODUCTION

The introduction is written with a robust command of sectoral data, presenting macro-level figures such as the livestock sector's contribution to GDP (12.54%), the spatial disparity between meat consumption in the Greater Jakarta area (6.12 kg/capita/year) and local livestock populations, the pressures of land conversion in peri-urban areas, and the risks—

ranging from the transmission of foot-and-mouth disease (FMD) to weight loss in livestock during transit to physical markets. Furthermore, the author explores the novelty of researching high-value living assets—commodities that, unlike horticultural products, require a higher degree of cognitive trust (BPS 2023). DKI Jakarta maintains a negligible livestock population (2,904 beef cattle and 1,322 sheep), placing heavy reliance on peri-urban hinterlands such as Bogor Regency (290,740 sheep and 99,191 goats), Tangerang (58,630 goats), and Bekasi (79,200 sheep). Crucially, these peri-urban production zones face rapid land conversion pressure, severely constricting physical farm space (Sujarwanta et al. 2024).

High market demand is further constrained by structural inefficiencies inherent in traditional livestock marketing. Traditional supply chains involve 3 to 4 intermediary nodes (smallholders, local collectors/*blantik*, wholesalers, and physical livestock markets). This market structure induces price information asymmetry, positioning smallholders as price takers with weak bargaining power (Hussam et al. 2025; Fauzi 2025). Price volatility and market uncertainty further exacerbate smallholder enterprise risk (Amam et al. 2025). In addition to economic inefficiencies, marketing live animals through physical livestock markets entails severe biological risks, including exposure to epizootic animal diseases such as Foot-and-Mouth Disease (FMD) (Febrianto et al. 2025), stress-induced mortality, and transit weight shrinkage of 5–10% during long-distance transportation.

Digital transformation through social media-based virtual livestock marketplaces (WhatsApp groups, Facebook Marketplace/groups, and Instagram) offers a strategic alternative channel (Gantini et al. 2025; Wahyuni et al. 2025). Digitalization facilitates structural economic power redistribution by establishing direct-to-consumer (D2C) channels between smallholders and end consumers or institutional buyers (e.g., Qurban committees and restaurants), eliminating middleman rent-seeking, restoring price sovereignty through real-time visual documentation of livestock quality, and acting as a non-contact biosecurity shield (Wolfert et al. 2017; Hasanah et al. 2025). This digital transition is supported by high internet penetration in metropolitan Jabodetabek (Yahya and Sugiyanto 2020; APJII 2023) and aligns with the national strategy for agricultural digitalization (e-Agriculture National Strategy) launched by FAO and the Ministry of Agriculture (FAO 2023).

However, digital technology adoption among smallholder livestock farmers encounters complex behavioral paradoxes. Unlike standardized, low-unit-value crop or horticultural produce (Geng et al. 2024), ruminant livestock represent high-value, heterogeneous, living capital assets. Remote digital transactions of live animals demand substantially higher cognitive trust, visual verification, and psychological readiness from farmers (Triatmojo et al. 2024; Hidayat et al. 2025). Despite high production potential, smallholders frequently exhibit adoption resistance due to digital literacy gaps and perceived technological complexity (Sugandini et al. 2023). Previous technology acceptance studies in agriculture have predominantly focused on crop farming or basic technology acceptance models like UTAUT without integrating user individual heterogeneity (age and income) as moderating variables, nor tracing the complete behavioral causal chain to downstream productivity and multidimensional sustainability outcomes (Venkatesh et al. 2012; Al-Emran 2023).

While previous studies have applied basic technology acceptance models (such as TAM or standard UTAUT) in crop farming or broad e-commerce settings, limited empirical research has investigated continued technology usage behavior among existing digital users in the high-value living asset (ruminant) sector. Furthermore, prior models often treat demographic variables as simple covariates rather than testing how individual heterogeneity (Age and Income) moderates the specific psychological pathways of UTAUT2, and how these behavioral patterns associate with farm productivity and multidimensional sustainability outcomes in a peri-urban context.

Based on the research background and theoretical framework, this study examines the relationships among the key determinants of technology adoption within the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework and their implications for agricultural productivity and business sustainability. Specifically, the study investigates the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on farmers' behavioral intention to adopt and use technology. In addition, it examines the direct influence of individual factors on behavioral intention and their moderating roles in the relationships between each UTAUT2 determinant and behavioral intention. This approach aims to provide a comprehensive understanding of how technology-related perceptions and individual characteristics interact in shaping farmers' intentions to adopt agricultural technologies.

Furthermore, this study explores the relationship between behavioral intention and actual use behavior, as well as the subsequent effects of technology use on farm productivity and business sustainability. By examining these relationships, the study seeks to establish how farmers' intentions translate into actual technology adoption and how such adoption contributes to improving agricultural productivity and supporting the long-term sustainability of farming operations. Ultimately, the research provides insights into the behavioral and individual factors that facilitate technology adoption and its potential contribution to sustainable agricultural development.

METHOD

Research Design and Sampling Procedure

This study adopts a quantitative research design utilizing a cross-sectional survey approach. Primary data collection was conducted between May and July 2026 across five administrative regions of Jabodetabek. To avoid selection bias, this study explicitly focuses on continued/intended use and usage behavior among existing digital users. The target population comprised smallholder ruminant farmers who actively utilized social media platforms for digital livestock marketing for a minimum of three months.

The methodology section specifies the inclusion criteria for farmers (having used social media for at least 3 months), the justification for the sample size (N = 200) based on a ratio of 5–10 observations per indicator for 34 indicators, a table showing the regional quota distribution (Table 1), and the procedure for evaluating the SEM-PLS model using SmartPLS 4. Sampling was executed via quota sampling based on regional farmer distribution (Table 1).

Table 1. Minimum Sample Quota Distribution by Study Area

Region	Population	Percentage (%)	Number of Respondents
DKI Jakarta	3,716	2,33	5
Bogor Regency and Bogor City	62,070	38,9	77
Depok City	2,663	1,67	4
Tangerang Regency and Tangerang City	45,494	28,51	57
Bekasi Regency and Bekasi City	45,607	28,58	57
Total	159,550	100,0	200

Source: Processed Data (2026)

Measurement Scale and Data Analysis Methods

Measurement items were adapted from validated UTAUT2 literature (Venkatesh et al. 2012) and customized for digital livestock marketing. All items were evaluated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The research instrument underwent pre-testing with 30 non-sample respondents using IBM SPSS to confirm initial face validity and scale reliability.

Data processing and hypothesis testing were performed using Structural Equation Modeling based on Partial Least Squares (SEM-PLS) via SmartPLS 4 software. Following Hair et al. (2021), the outer model was evaluated for convergent validity, internal consistency, and discriminant validity. PLS-SEM was chosen due to its superior capabilities in handling complex prediction-oriented model structures with moderating interaction terms, non-normal data distributions, and composite latent variables (Hair et al. 2021; Chin 1998). The analytic procedure encompassed:

1. Descriptive Analysis: Evaluating demographic profiles and indicator mean scores against Sugiyono's (2020) class interval ranges.
2. Measurement Model Assessment (Outer Model): Assessing indicator reliability (outer loadings > 0.70), convergent validity (Average Variance Extracted/AVE > 0.50), internal consistency reliability (Cronbach's Alpha and Composite Reliability *rho_a*, *rho_c* > 0.70), and discriminant validity via the Fornell-Larcker criterion (Hair et al. 2021).
3. Structural Model Assessment (Inner Model): Evaluating coefficients of determination (R^2), path coefficients, and statistical significance via a non-parametric bootstrapping procedure with 5,000 resamples (t > 1.96, p < 0.05). Moderation interaction effects were modeled using the two-stage product-indicator approach.

The extended conceptual framework integrating UTAUT2 constructs, Individual Factors moderation, and downstream outcomes is depicted in Figure 1.

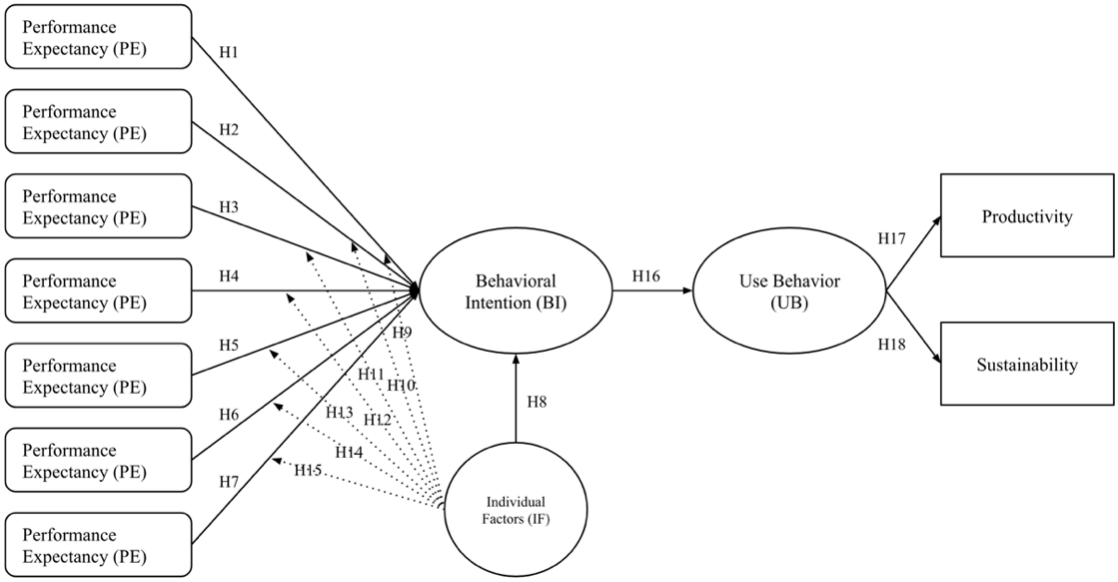


Figure 1. Conceptual Framework

RESULT AND DISCUSSION

Respondent Socio-Demographic Characteristics and Farm Profiles

Descriptive statistical analysis of the 200 surveyed ruminant livestock farmers provides a rich empirical profile and strategic insights into smallholder farming operations in peri-urban Jabodetabek. As emphasized by Sujarwanta et al. (2024) and Febrianto et al. (2025), smallholder ruminant management in Indonesia is heavily dominated by male labor due to the intense physical demands of livestock handling, forage harvesting (ngarit), and stall maintenance accordingly, the sample was overwhelmingly male (98.5%), while females comprised 1.5%. Age distribution was predominantly concentrated in mature and senior brackets, led by farmers aged 40–49 years (29.0%) and 50–59 years (26.0%), followed by 30–39 years (23.5%), 20–29 years (15.5%), and > 60 years (6.0%).

In line with findings by Triatmojo et al. (2024) and Kai et al. (2025), this demographic structure reflects national livestock trends where mature producers command production owing to superior capital accumulation, established buyer networks, and risk-bearing capacity required for high-value living assets. Educational attainment was notably high for smallholder agriculture, with senior high school graduates constituting 38.0% and tertiary diploma/bachelor's degree holders comprising 29.5%, followed by junior high school (20.5%) and elementary school (12.0%). As observed by Hidayat et al. (2025) and Wahyuni et al. (2025), high formal education in peri-urban environments significantly lowers cognitive entry barriers, fostering rapid digital literacy and smartphone adoption for agribusiness marketing.

Regarding operational farm profiles, more than half of the respondents operated on severely restricted land footprints of less than 100 m² (51.5%), while 32.5% managed 100–500 m², and only 16.0% possessed land areas exceeding 500 m². Herd ownership was concentrated in medium smallholder scales of 25–49 animals (36.5%), followed by < 25 animals (26.5%), 50–100 animals (24.5%), and > 100 animals (12.5%).

Economically, the largest proportion reported a monthly turnover income of IDR 5,000,001 to 7,000,000 (31.0%), followed by IDR 7,000,001 to 10,000,000 (27.0%), $\le$ IDR 5,000,000 (24.0%), and > IDR 10,000,000 (18.0%). Household sizes were predominantly 4–5 members (43.0%), followed by > 5 members (34.5%) and 1–3 members (22.5%). Notably, 55.5% of respondents possessed extensive digital marketing experience exceeding 3 years using social media for livestock sales, while 28.5% had 1–3 years, and 16.0% had 3 months to 1 year, confirming that social media marketing has evolved into a mature, routine commercial habit in Jabodetabek (Yahya and Sugiyanto 2020; Gantini et al. 2025).

A pivotal analytical insight centers on the land area constraint: 51.5% of smallholders operate on farm footprints below 100 m². According to Saragih et al. (2023) and Sujarwanta et al. (2024), this empirical reality captures acute peri-urban spatial squeeze driven by rapid urban real estate conversion, forcing smallholders into intensive stall-feeding zero-grazing production systems within residential yards. Because physical herd expansion is geographically bounded (36.5% maintain 25–49 head), smallholder economic rationality shifts from land-scale expansion toward marketing margin optimization.

In this context, as highlighted by Hussam et al. (2025) and Amam et al. (2025), virtual livestock market adoption serves as a strategic disintermediation tool, allowing smallholders to bypass middleman price suppression, capture direct-to-consumer price premiums of 20–30% during peak religious cycles like Qurban, and maximize net profit per live animal without expanding physical farm footprint.

Descriptive Analysis of Research Variables

Descriptive evaluation based on Sugiyono's (2020) 5-point Likert class interval (range 0.80) illustrates positive perception tendencies across all model constructs (Table 2).

Tabel 2. Minimum Sample Quota Distribution by Study AreaQuota Distribution by Study Area

Code	Laten Variable	Mean Score	Perception Category
IF	Individual Factors	3.430	High
PE	Performance Expectancy	3.758	High
EE	Effort Expectancy	3.746	High
SI	Social Influence	3.748	High
FC	Facilitating Conditions	3.783	High
HM	Hedonic Motivation	3.751	High
PV	Price Value	3.786	High
HB	Habit	3.754	High
BI	Behavioral Intention	3.763	High
UB	Use Behavior	3.778	High

Code	Laten Variable	Mean Score	Perception Category
P	Productivity	3.771	High
SI	Sustainability	3.772	High

Source: Processed Data (2026)

As detailed in Table 2, Price Value (3.786) and Facilitating Conditions (3.783) achieved the highest mean perception scores. This indicates a strong consensus among smallholders that digital marketing costs (internet data packages) are negligible compared to profit margin gains from disintermediation. Furthermore, high Facilitating Conditions confirm universal mobile connectivity in peri-urban Jabodetabek. High Behavioral Intention (3.763) translates effectively into routine Use Behavior (3.778), which smallholders strongly associate with elevated Farm Productivity (3.771) and Business Sustainability (3.772).

SEM-PLS Empirical Results

1. Measurement Model Assessment (Outer Model)

Following Hair et al. (2021), the outer model was evaluated to verify indicator reliability, convergent validity, internal consistency, and discriminant validity. Convergent validity requires indicator outer loadings > 0.70 and Average Variance Extracted (AVE) > 0.50. As shown in Figure 2, all 34 measurement indicators and moderation interaction terms displayed outer loadings well above 0.70, eliminating the need for item deletion.

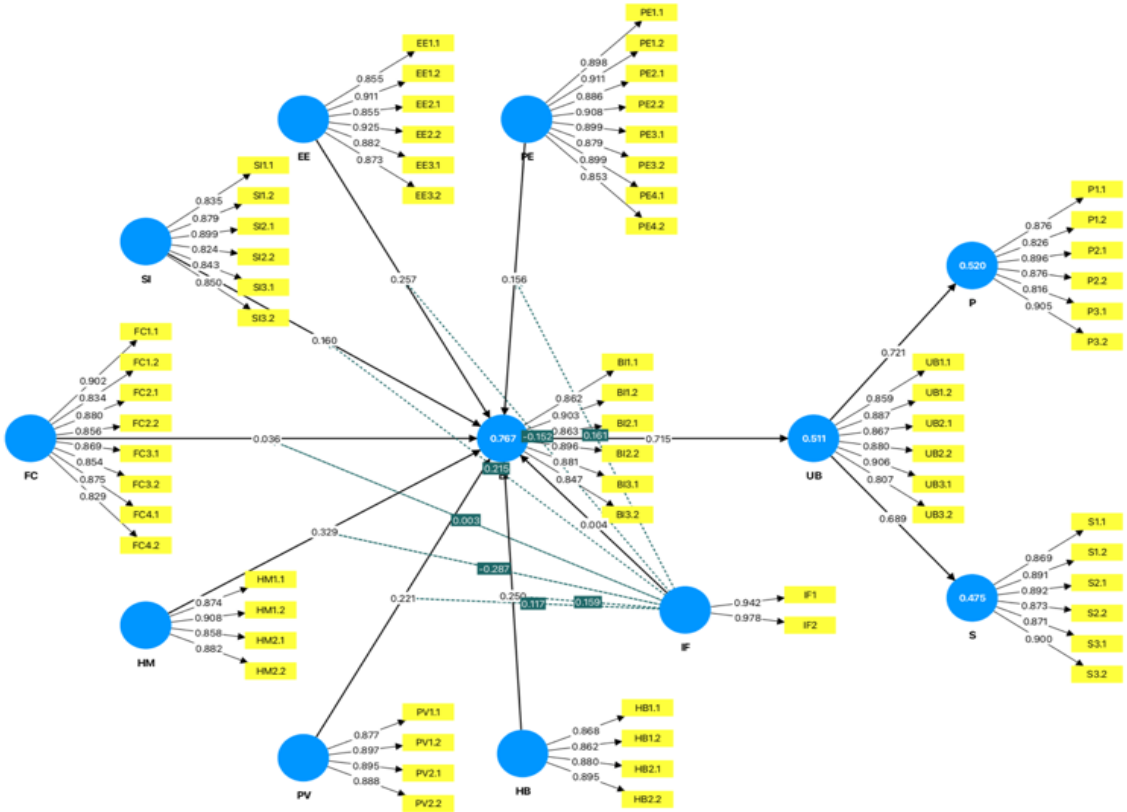


Figure 2. Outer Loadings and Measurement Model Output

Convergent validity and scale reliability parameters are summarized in Table 3. All latent constructs fulfilled the AVE threshold (> 0.50), ranging from 0.731 (SI) to 0.922 (IF). Cronbach's Alpha and Composite Reliability (*rho_a, rho_c*) exceeded 0.70 across all constructs, confirming high internal consistency.

Table 3. Convergent Validity and Scale Reliability Parameters

Variabel	Cronbach's Alpha	CR (rho_a)	CR (rho_c)
Individual Factors (IF)	0.920	1.071	0.959
Performance Expectancy (PE)	0.963	0.965	0.969
Effort Expectancy (EE)	0.944	0.949	0.955
Social Influence (SI)	0.926	0.931	0.942
Facilitating Conditions (FC)	0.951	0.956	0.959
Hedonic Motivation (HM)	0.904	0.913	0.933
Price Value (PV)	0.912	0.917	0.938
Habit (HB)	0.900	0.903	0.930
Behavioral Intention (BI)	0.939	0.939	0.952
Use Behavior (UB)	0.934	0.938	0.948
Productivity (P)	0.933	0.934	0.948
Sustainability (S)	0.943	0.944	0.955

Source: Processed Data (2026)

Discriminant validity was confirmed using the Fornell-Larcker criterion (Table 4). In accordance with Henseler et al. (2015) and Hair et al. (2021), the square root of AVE for each construct (bold diagonal values) strictly exceeded its correlation with all other construct pairs, establishing robust empirical distinctiveness. In addition to the Fornell-Larcker criterion, Heterotrait-Monotrait (HTMT) ratios were computed to ensure discriminant validity. All HTMT values remained below the conservative threshold of 0.85 (Henseler et al. 2015), confirming distinct constructs.

Table 4. Discriminant Validity Assessment via Fornell-Larcker Criterion

	BI	EE	FC	HB	HM	IF	P	PE	PV	S	SI	UB
BI	0.876											
EE	0.447	0.884										
FC	0.307	0.101	0.863									
HB	0.457	0.176	0.198	0.877								
HM	0.508	0.123	0.261	0.211	0.881							
IF	-0.119	-0.074	-0.150	-0.078	-0.149	0.960						
P	0.662	0.277	0.366	0.448	0.443	-0.149	0.866					
PE	0.353	0.258	0.173	0.134	0.177	-0.027	0.200	0.892				
PV	0.437	0.172	0.163	0.186	0.276	-0.091	0.284	0.122	0.889			
S	0.629	0.259	0.390	0.384	0.415	-0.114	0.730	0.379	0.233	0.883		
SI	0.399	0.158	0.219	0.196	0.208	-0.045	0.286	-0.012	0.076	0.212	0.855	
UB	0.715	0.315	0.512	0.578	0.395	-0.170	0.721	0.229	0.346	0.689	0.273	0.868

Source: Processed Data (2026)

2. Structural Model Assessment (Inner Model)

The structural model was evaluated using the coefficient of determination (R^2) and path coefficient estimation. The R^2 value measures the explanatory power of the exogenous constructs in predicting the endogenous constructs. According to Hair et al. (2019), R^2 values greater than 0.75 indicate substantial explanatory power, values around 0.50 indicate moderate explanatory power, and values below 0.25 indicate weak explanatory power. Model explanatory power was confirmed via R^2: Behavioral Intention (R^2 = 0.767), Productivity (R^2= 0.520), Use Behavior (R^2= 0.511), and Sustainability (R^2 = 0.475). To verify predictive relevance beyond sample explained variance, Q^2 values derived from PLSpredict exceeded 0 (ranging from 0.35 to 0.58), confirming satisfactory predictive capability. These findings suggest that the proposed model is highly effective in explaining farmers' behavioral intentions and provides adequate predictive capability for actual technology use and its subsequent impacts.

Hypothesis testing was conducted using the bootstrapping procedure in PLS-SEM by examining the path coefficients, t-statistics, and p-values. Following Hair et al. (2019), a hypothesis was considered statistically significant when the t-statistics exceeded 1.96 and the p-value was less than 0.05. The results indicate that 15 out of the 18 proposed hypotheses were supported, while three hypotheses were not supported, as summarized in Table 5.

Tabel 5. Structural Path Coefficients and Hypothesis Testing Results

Hip	Structural Path	*Path Coefficient (β)*	*T Statistics (|O/STDEV|)*	*P-Value*	Decision
H1:	PE → BI	0,156	3,747	0,000	Supported
H2:	EE → BI	0,257	4,900	0,000	Supported
H3:	SI → BI	0.160	3.756	0.000	Supported
H4:	FC → BI	0.036	1.053	0.293	Not supported
H5:	HM → BI	0.329	6.443	0.000	Supported
H6:	PV → BI	0.221	5.421	0.000	Supported
H7:	HB → BI	0.250	6.431	0.000	Supported
H8:	IF → BI	0.004	0.076	0.939	Not supported
H9:	IF x PE → BI	0.161	3.275	0.001	Supported
H10:	IF x EE → BI	-0.152	3.269	0.001	Supported
H11:	IF x SI → BI	0.215	3.686	0.000	Supported
H12:	IF x FC → BI	0.003	0.064	0.949	Not supported
H13:	IF x HM → BI	-0.287	4.647	0.000	Supported
H14:	IF x PV → BI	0.117	2.802	0.005	Supported
H15:	IF x HB → BI	0.159	3.800	0.000	Supported
H16:	BI → UB	0.715	20.581	0.000	Supported
H17:	UB → P	0.721	24.045	0.000	Supported
H18:	UB → S	0.689	21.463	0.000	Supported

Source: Processed Data (2026)

Comprehensive Discussion

1. Effects of the Core UTAUT2 Constructs on Behavioral Intention (H1, H2, H3, H5, H6, and H7 Supported)

Empirical testing confirms that six core UTAUT2 constructs significantly drive smallholder adoption intention. Crucially, Hedonic Motivation (HM) emerged as the single most powerful predictor of behavioral intention ($\beta = 0.329$, $t = 6.443$, $p < 0.001$).

As argued by Venkatesh et al. (2012) and Alalwan et al. (2017), this finding reveals a profound insight: technology adoption in smallholder livestock farming is not purely governed by cold economic rationality but is heavily driven by intrinsic emotional gratification. Ruminant livestock farming is physically grueling. Utilizing interactive social media platforms, capturing video footage of prize bulls/goats, uploading visual livestock showcases, and receiving instant peer feedback, "likes," and comments, introduces gamified socio-emotional enjoyment and pride of ownership, transforming tedious marketing chores into creative activities.

Effort Expectancy ($\beta = 0.257$, $t = 4.900$) and Habit ($\beta = 0.250$, $t = 6.431$) represent the second and third strongest direct drivers. As noted by Limayem et al. (2007), because smallholders utilize ubiquitous social media applications (WhatsApp and Facebook) already embedded in daily communication, software interaction involves zero learning curve friction, seamlessly transitioning into routine marketing habits. Price Value ($\beta = 0.221$, $t = 5.421$), Social Influence ($\beta = 0.160$, $t = 3.756$), and Performance Expectancy ($\beta = 0.156$, $t = 3.747$) complete adoption motivation. Smallholders perceive internet data costs as minor relative to disintermediation margin gains (Zeithaml 1988), while peer endorsement in farmer groups provides crucial community validation (Michels et al. 2020).

2. Infrastructure Saturation and Non-Significant Direct Effects (H4 and H8 Rejected)

Hypothesis testing indicates that Facilitating Conditions (FC → BI, p = 0.293) and direct Individual Factors (IF → BI, p = 0.939) have no statistically significant direct impact on adoption intention, leading to the rejection of H4 and H8.

The non-significance of Facilitating Conditions confirms the Infrastructure Saturation Hypothesis. In peri-urban Jabodetabek, 4G/5G connectivity and smartphone access are universally available. We describe this outcome under the *Infrastructure Saturation Hypothesis*: facilitating infrastructure acts as a mandatory baseline condition rather than a direct adoption driver. Consequently, technical infrastructure has evolved from an innovation driver into a neutral baseline prerequisite (a hygiene factor in Herzberg's terminology). Mobile internet availability is necessary but no longer possesses differential motivating power to trigger adoption intention. As demonstrated by Molina-Maturano et al. (2021), once technological access becomes universal, adoption intentions are dictated by internal intrinsic motivation and perceived value.

Demographic characteristics alone do not directly dictate intent; rather, they alter the sensitivity of farmers to psychological drivers (UTAUT2 constructs). Likewise, demographic attributes alone (age and income) do not directly dictate technology uptake. However, these individual characteristics play a vital moderating role when interacting with UTAUT2 pathways.

3. Interaction Mechanisms of Individual Factors Moderation (H9–H15 Supported)

Moderation analysis via the two-stage product-indicator approach confirms that Individual Factors (combined age and income level) significantly moderate 6 out of 7 UTAUT2 pathways leading to Behavioral Intention (H9, H10, H11, H13, H14, H15 supported; H12 rejected due to FC non-significance).

In-depth structural evaluation of these interaction paths highlights key generational and socio-economic dynamics:

1. Negative Moderation on Hedonic Motivation (H13: IF x HM → BI, $\beta = -0.287$, $t = 4.647$, $p < 0.001$): The highly significant negative interaction coefficient demonstrates that Hedonic Motivation's influence on adoption intention weakens as farmer age and income level increases. Hedonic enjoyment drives intention more strongly among younger/lower-income smallholders. As age and income increase, adoption becomes strictly governed by pragmatic economic performance. Conversely, hedonic fun serves as an exceptionally potent adoption engine for younger, lower-income smallholders. For older, economically established farmers, social media entertainment is irrelevant; their adoption decisions are strictly dictated by pragmatic business efficiency.
2. Negative Moderation on Effort Expectancy (H10: IF x EE → BI, $\beta = -0.152$, $t = 3.269$, $p = 0.001$): Application usability and interface simplicity exert a stronger influence on younger, lower-income smallholders. Apps are easy to use and are critical for younger producers. Older/higher-income farmers show less sensitivity to complex UIs, as they often delegate technological navigation to family members or younger hired labor. Younger farmers demand seamless, rapid app navigation. Senior, higher-income farmers are less deterred by initial software complexity; if profit returns are proven, wealthy senior farmers readily hire tech-savvy youth or enlist family members to manage app operations.
3. Positive Moderation on Social Influence (H11: IF x SI → BI, $\beta = 0.215$, $t = 3.686$, $p < 0.001$): A positive interaction coefficient confirms that Social Influence's impact on adoption intention strengthens significantly among senior, higher-income farmers. Senior smallholders hold prominent social standing in local farmer associations. They are highly sensitive to social status, institutional legitimacy, and peer leadership endorsements.

Social network validation is a mandatory prerequisite for senior farmers before transitioning trade channels online.

4. Positive Moderation on Performance Expectancy (H9: $\beta = 0.161$, $p = 0.001$), Price Value (H14: $\beta = 0.117$, $p = 0.005$), and Habit (H15: $\beta = 0.159$, $p < 0.001$): As farmer age and income rise, Performance Expectancy and Price Value become increasingly dominant drivers. Peer validation and institutional leadership significantly drive intention among older, higher-income producers who value social standing in farmer associations. Senior, established farmers exhibit pragmatic adoption behavior, their intentions are driven by tangible empirical proof of accelerated inventory turnover and higher net liveweight prices.

As demonstrated by Kai et al. (2025) and Pienwisetkaew et al. (2023), these moderating insights validate the Individual Heterogeneity in Technology Adoption theory, confirming that agricultural technology diffusion cannot employ a one-size-fits-all approach, but demands demographically segmented intervention strategies.

4. Effects of Behavioral Intention on Actual Use, Productivity, and Sustainability (H16, H17, and H18 Supported)

The structural model demonstrates that digital marketplace usage is strongly and positively associated with farm productivity (beta = 0.721) and business sustainability (beta = 0.689). Because cross-sectional data measures associations at a single point in time, these relationships reflect positive correlations rather than definitive longitudinal causal impacts. At the implementation stage, a strong Behavioral Intention was consistently translated into actual technology usage. The emergence of virtual livestock marketplaces has become increasingly integrated into the marketing supply chain of ruminant farmers in the Greater Jakarta Metropolitan Area, supporting the technology adoption framework proposed by Venkatesh et al. (2012) and the empirical findings of Thimthong et al. (2026). Furthermore, the use of digital platforms significantly enhanced farmers' Productivity by reducing dependence on intermediaries and enabling higher profit margins through direct market access (Blocher et al. 2000). More broadly, the digital marketing ecosystem contributed substantially to the Sustainability of smallholder livestock farming by strengthening economic resilience, expanding inclusive social networks, and improving environmentally efficient logistics. These findings are consistent with the principles of sustainable agricultural development proposed by Sarkar et al. (2021) and Al-Emran (2023).

Managerial and Policy Implications

This study advances agribusiness technology management literature by validating the extended UTAUT2 model with individual moderation in peri-urban ruminant livestock farming. Practical implications target three key stakeholders:

1. For Government Agencies (Ministry of Agriculture & Regional Livestock Services): Formulate tiered digital literacy programs customized by age segments and establish digital livestock health certification to build online transaction trust.
2. For Agritech Startups & Platform Developers: Design intuitive, visual UI/UX catering to Hedonic Motivation and Effort Expectancy, integrated with seller verification, escrow payment services, and visual liveweight estimation tools for senior farmers.
3. For Farmer Associations: Leverage social influence through peer-to-peer learning networks and form online marketing consortia to bolster smallholder bargaining power.

CONCLUSIONS AND RECOMMENDATIONS

Conclusion

This study demonstrates that the adoption of virtual livestock marketplaces among smallholder ruminant farmers in Jabodetabek is shaped by the interaction of technological

perceptions, individual characteristics, and behavioral factors within the UTAUT2 framework. The respondents were predominantly male (98.5%), aged 40–49 years (29.0%) and had completed high school education (38.0%). Most respondents operated on relatively restricted landholdings of less than 100 m² (51.5%), maintained medium-sized herds of 25–49 head (36.5%), earned monthly incomes of IDR 5–7 million (31.0%), and had more than three years of digital marketing experience (55.5%).

The structural model explains 76.7% of the variance in Behavioral Intention (BI), indicating substantial explanatory power. Hedonic Motivation emerged as the strongest determinant of adoption intention, followed by Effort Expectancy, Habit, Price Value, Social Influence, and Performance Expectancy. In contrast, Facilitating Conditions and the direct effect of Individual Factors were not statistically significant, potentially reflecting the relatively established digital infrastructure in the peri-urban study area. Nevertheless, Individual Factors, particularly age and income, significantly moderate six of the seven relationships between UTAUT2 constructs and Behavioral Intention. Furthermore, Behavioral Intention strongly predicted actual Use Behavior ($\beta = 0.715$), which subsequently contributed to Farm Productivity ($R^2 = 0.520$) and Business Sustainability ($R^2 = 0.475$). These findings highlight the importance of integrating technology acceptance, individual characteristics, and actual usage behavior to understand the contribution of digital marketplaces to agricultural productivity and the sustainability of smallholder livestock enterprises.

Research Limitations

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the cross-sectional research design captures farmers' perceptions and technology adoption behavior at a single point in time. Consequently, it cannot fully explain changes in behavioral intention, technology usage patterns, or the long-term effects of digital marketplace adoption on farm productivity and business sustainability. Second, the study focuses on existing users or farmers with prior exposure to digital marketing. Therefore, the findings may not adequately represent non-users, technology-resistant farmers, or smallholders who face greater barriers to digital adoption. This limits the generalizability of the findings across different stages of technology adoption. Third, the geographical scope is restricted to the Jabodetabek area, which is characterized by relatively developed digital infrastructure and access to technology compared with more remote rural agricultural regions. Accordingly, the findings may not fully reflect the adoption dynamics of smallholder livestock farmers operating in rural areas with different socioeconomic, infrastructural, and institutional conditions.

Recommendations

Future digital adoption interventions should implement demographically segmented strategies by targeting younger smallholders through visual, gamified digital content to leverage hedonic motivation, while simultaneously supporting senior farmers through verified transaction security mechanisms and community leadership endorsements. For future research in agribusiness technology management, scholars are encouraged to investigate virtual marketplace acceptance across purely rural agricultural hinterlands, conduct longitudinal evaluations to observe adoption evolution over time, and apply mixed methods designs to capture smallholders' deeper cognitive decision-making processes.

Author Contributions

The first author conducted conceptualization, data collection, statistical modeling, and manuscript drafting. The second and third authors contributed to theoretical framework

formulation, statistical verification, and critical manuscript revision. All authors approved the final submitted version.

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