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Determinants of cattle productivity under the UPSUS SIWAB program in Buru Regency

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ABSTRACT

The UPSUS SIWAB program was introduced to improve bovine reproductive performance and cattle productivity through artificial insemination (AI), feed support, and stronger farmer capacity. Lolong Guba District is an important program implementation area in Buru Regency, Maluku Province, but the factors associated with productivity among participating farmers have not been clearly established. This study described participant farm profiles and analyzed the determinants of cattle productivity. A cross-sectional survey was conducted from 25 January to 25 February 2026 among 60 cattle farmers drawn from a population of 206. Primary data were obtained through interviews, field observations, and documentation, while secondary data were compiled from relevant government agencies. The relationships among land tenure rights, the availability of AI inputs and feed, farmer knowledge, and cattle productivity were evaluated using partial least squares structural equation modeling. Most respondents had completed elementary school (65.0%), and 71.7% combined crop farming with cattle raising. The structural model explained 37.7% of the variance in cattle productivity (adjusted $R^2 = 0.344$). AI-input and feed availability positively affected farmer knowledge ($\beta = 0.486$, $t = 4.012$, $p < 0.001$), while farmer knowledge positively affected cattle productivity ($\beta = 0.548$, $t = 4.550$, $p < 0.001$). The other modeled paths were not significant. These findings indicate that reliable input delivery should be integrated with practical reproductive-management education to improve program outcomes.

INTRODUCTION

Increasing cattle productivity is central to the sustainability of smallholder livestock systems because reproductive performance determines herd growth, the regularity of animal sales, and the availability of replacement stock. In Indonesia, however, productivity is often constrained by uneven access to breeding services, inconsistent feed supply, limited reproductive management, and weak coordination among service providers. Technical guidance on beef-cattle mating management emphasizes accurate heat detection, timely breeding, and appropriate reproductive recording [1]. Reliable forage provision and the use of local feed resources are equally important for maintaining animal condition and reproductive performance [2,3]. These production and service constraints have long shaped the research and development agenda for Indonesian beef cattle [4].

The Special Effort to Accelerate the Population of Pregnant Cows (UPSUS SIWAB) program was designed to address these constraints by integrating artificial insemination (AI), pregnancy services, feed support, and farmer assistance. Evidence from several Indonesian regions indicates that program performance depends not only on the availability of semen and inseminators but also on adoption by farmers, service timeliness, and local implementation capacity [5–8]. Evaluations have also considered the economic benefits of UPSUS SIWAB and its contribution to livestock development [9]. More broadly, the application of breeding technology and the effectiveness of AI are influenced by management quality, institutional support, and farmer knowledge [10,11].

Maluku Province set annual UPSUS SIWAB targets of 3,200 cows in 2017, 3,250 in 2018, 3,237 in 2019, and 2,768 in 2020. Buru Regency accounted for one of the province's largest program allocations: 1,958 cows in 2017, 1,500 in 2018, 1,000 in 2019, and 1,068 in 2020. Thus, 5,526 of the 12,455 cows targeted in Maluku during 2017–2020 (44.37%) were located in Buru Regency [16]. These figures make Buru an important setting for examining how program inputs and farmer-level capabilities are associated with cattle productivity.

Within Buru Regency, Lolong Guba District is a major UPSUS SIWAB implementation center and the location where the regency government first established an AI service post. The district has trained insemination personnel and basic service infrastructure. From 2017 to 2020, the district recorded an AI target of 1,359 cows and 1,116 births [16]. Nevertheless, implementation challenges remain. Reproductive-disorder management requires specialized skills, AI containers and related facilities are not always continuously available at the regency depot, and farmers' knowledge of reproductive problems, sexual maturity, and estrus detection is uneven. Sustainable feed availability and cross-sector coordination also remain important concerns.

Previous program evaluations have largely described AI achievement, adoption, or economic benefits, while less attention has been given to the pathway through which input availability and farmer knowledge jointly shape productivity in Lolong Guba. Accordingly, this study asked which factors determine cattle productivity among UPSUS SIWAB participants in Buru Regency. Its objectives were to

(1) describe the profiles of participating cattle farmers and their enterprises and (2) analyze the relationships among land tenure rights, the availability of AI inputs and feed, farmer knowledge, and cattle productivity. By clarifying both direct and indirect relationships, the study is expected to inform more integrated delivery of inputs and extension services.

MATERIALS AND METHODS

Research site and time

The study was conducted in Lolong Guba District, Buru Regency, Maluku Province, Indonesia, from 25 January to 25 February 2026. The district was selected because it is a principal UPSUS SIWAB implementation area and has an established AI service post. The research used a quantitative, cross-sectional survey design to describe farmer characteristics and estimate the relationships among the constructs included in the cattle-productivity model.

Population, sample, and data collection

Administrative records from the Maluku Provincial Agriculture Office identified 206 cattle farmers in the study population. The study used 60 respondents, equivalent to approximately 30% of that population. Respondents were cattle farmers participating in or associated with UPSUS SIWAB activities in Lolong Guba District. The unit of analysis was the individual farmer or farm household. Because the source survey documentation did not report a probability-based selection procedure, the findings should be interpreted as evidence for the surveyed participants rather than as population-wide causal estimates.

Primary data were obtained through farmer interviews, direct field observation, and documentation of relevant farm and program conditions. The questionnaire captured respondent education, age, farming experience, principal occupation, and indicators representing the four latent constructs. Secondary information was compiled from Statistics Indonesia offices for Maluku Province and Buru Regency, the provincial and regency agriculture offices, and the Lolong Guba District administration. Data were checked for completeness before descriptive and model-based analysis.

Research framework and variables

The conceptual model contained four constructs: land tenure rights, availability of AI inputs and feed, farmer knowledge, and cattle productivity. Land tenure rights were represented by five indicators (LTR1–LTR5). Input availability was represented by the timeliness or adequacy of AI inputs and feed availability. Farmer knowledge was represented by knowledge of reproductive disorders and knowledge of sexual maturity and estrus. Cattle productivity was represented by three retained productivity indicators (PROD2–PROD4). The hypothesized model included paths from land tenure rights to input availability, farmer knowledge, and productivity; from input availability to farmer knowledge and productivity; and from farmer knowledge to productivity. The complete framework is shown in Figure 1.

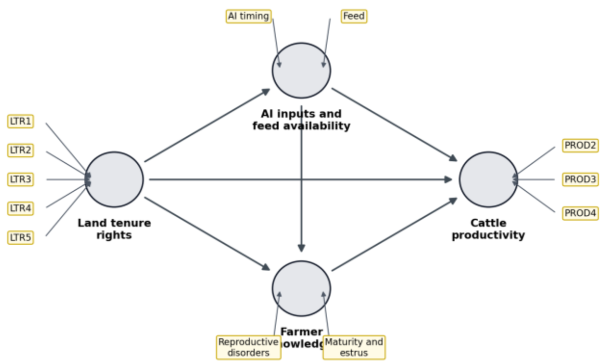

Figure 1. Conceptual model of cattle productivity under UPSUS SIWAB.

Data analysis

Respondent characteristics were summarized using frequencies and percentages. The hypothesized relationships were evaluated with partial least squares structural equation modeling (PLS-SEM), an approach suitable for prediction-oriented models with latent constructs [12,15]. Measurement-model assessment considered indicator loadings, average variance extracted (AVE), composite reliability, cross-loadings, and the Fornell–Larcker criterion [13,14]. In accordance with the exploratory orientation of the study, retained indicator loadings were evaluated against a minimum value of 0.60; AVE values above 0.50 indicated convergent validity, and composite reliability values above 0.70 indicated acceptable internal consistency. Variance inflation factors (VIFs) were examined for collinearity.

The structural model was evaluated using path coefficients, t statistics, p values, coefficients of determination (R^2 and adjusted R^2), and effect sizes (f^2). Statistical significance was assessed at $p < 0.05$. The magnitude of R^2 was interpreted in relation to the model's explanatory orientation [12], while f^2 values were used to describe the relative contribution of predictor constructs. Because the design was cross-sectional and nonexperimental, path coefficients were interpreted as modeled associations rather than definitive causal effects.

RESULTS

Respondent profile

Respondents generally had limited formal education. As shown in Table 1, 65.0% had completed elementary school, 13.3% junior high school, and 15.0% senior high school; only one respondent (1.7%) had completed higher education. The age distribution was concentrated in the older working-age groups: 58.3% were 40–54 years old, while 6.7% were older than 64 years (Table 2).

Table 1. Distribution of respondents by educational attainment

No.	Educational attainment	Frequency (n)	Percent (%)
1	No schooling	3	5.0
2	Elementary school	39	65.0
3	Junior high school	8	13.3
4	Senior high school	9	15.0
5	Higher education	1	1.7
	Total	60	100.0

Source: Primary data (2026).

Table 2. Distribution of respondents by age

No.	Age (years)	Frequency (n)	Percent (%)
1	<30	2	3.3
2	30–34	6	10.0
3	35–39	6	10.0
4	40–44	12	20.0
5	45–49	9	15.0
6	50–54	14	23.3
7	55–59	4	6.7
8	60–64	3	5.0
9	>64	4	6.7
	Total	60	100.0

Source: Primary data (2026).

Livestock-enterprise experience was substantial. Half of the respondents had raised livestock for at least 20 years, including 33.3% with 20–24 years of experience and 16.7% with more than 24 years (Table 3). Interviews indicated that several respondents had begun farming after joining the transmigration program from Java to Buru Island in the 1980s. Most respondents combined crop farming and cattle raising (71.7%), while smaller shares combined farming with services, trade, or industry (Table 4).

Table 3. Distribution of respondents by livestock-farming experience

No.	Experience (years)	Frequency (n)	Percent (%)
1	<5	4	6.7
2	5–9	13	21.7

No.	Experience (years)	Frequency (n)	Percent (%)
3	10–14	10	16.7
4	15–19	3	5.0
5	20–24	20	33.3
6	>24	10	16.7
	Total	60	100.0

Source: Primary data (2026).

Table 4. Distribution of respondents by principal occupation

No.	Occupation	Frequency (n)	Percent (%)
1	Farmer–livestock raiser	6	10.0
2	Farmer + livestock raiser	43	71.7
3	Farmer + industry worker	1	1.7
4	Farmer + trader	1	1.7
5	Farmer + service worker	8	13.3
6	Farmer + livestock raiser + service worker	1	1.7
	Total	60	100.0

Source: Primary data (2026).

Measurement model

All retained indicators had loadings of at least 0.641 on their intended constructs (Figure 2 and Table 6). The square roots of AVE on the diagonal of the Fornell–Larcker matrix exceeded the corresponding interconstruct correlations (Table 5), and each indicator loaded most strongly on its intended construct (Table 6). AVE values ranged from 0.564 to 0.645, while composite reliability ranged from 0.717 to 0.900 (Table 7). However, Cronbach's alpha was low or negative for several constructs, indicating that the internal-consistency results should be interpreted cautiously. All reported VIF values were below the study's prespecified threshold of 10, although the value of 7.409 for LTR4 indicates comparatively high collinearity (Table 8).

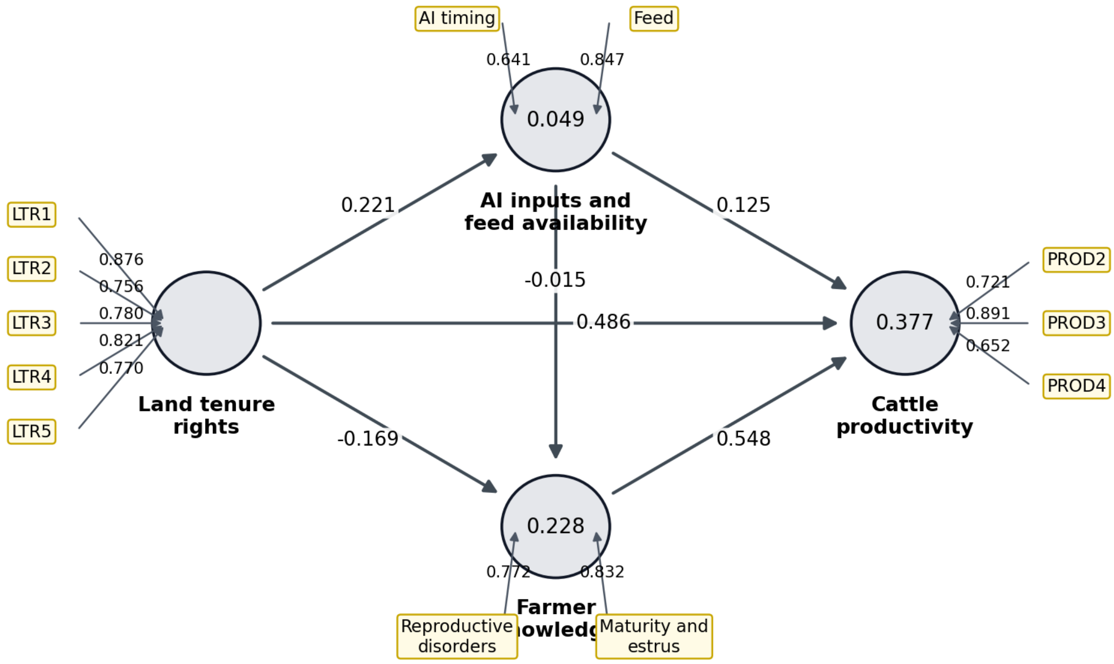

Figure 2. PLS-SEM outer model for cattle productivity.

Table 5. Fornell–Larcker criterion

Construct	Land tenure rights	AI inputs and feed	Farmer knowledge	Cattle productivity
Land tenure rights	0.802			
AI inputs and feed	0.221	0.751		
Farmer knowledge	−0.061	0.449	0.803	
Cattle productivity	−0.020	0.367	0.605	0.762

Note: Diagonal values are the square roots of AVE. Source: Primary data (2026).

Table 6. Indicator cross-loadings

Indicator	Land tenure rights	AI inputs and feed	Farmer knowledge	Cattle productivity
AI timing	0.201	0.641	0.227	0.235
Feed	0.146	0.847	0.422	0.311
LTR1	0.876	0.168	−0.131	−0.154
LTR2	0.756	0.278	0.071	0.082
LTR3	0.780	0.132	−0.037	0.064
LTR4	0.821	0.136	−0.092	−0.035
LTR5	0.770	−0.009	−0.190	−0.069
PROD2	0.179	0.475	0.417	0.721

Indicator	Land tenure rights	AI inputs and feed	Farmer knowledge	Cattle productivity
PROD3	−0.103	0.269	0.592	0.891
PROD4	−0.152	0.022	0.317	0.652
Reproductive disorders	−0.046	0.466	0.772	0.346
Maturity and estrus	−0.052	0.269	0.832	0.609

Source: Primary data (2026).

Table 7. Construct reliability and convergent validity

Construct	Cronbach's α	rho_A	Composite reliability	AVE
Land tenure rights	0.876	0.897	0.900	0.643
AI inputs and feed	0.236	0.254	0.717	0.564
Farmer knowledge	−0.450	0.455	0.784	0.645
Cattle productivity	−0.640	0.705	0.803	0.580

Source: Primary data (2026).

Table 8. Variance inflation factors

Indicator	VIF
AI timing	1.018
Feed	1.018
LTR1	2.571
LTR2	1.719
LTR3	3.684
LTR4	7.409
LTR5	5.371
PROD2	1.211
PROD3	1.650
PROD4	1.409
Reproductive disorders	1.092
Maturity and estrus	1.092

Source: Primary data (2026).

Structural model

The model explained 37.7% of the variance in cattle productivity (adjusted $R^2 = 0.344$), 22.8% of the variance in farmer knowledge (adjusted $R^2 = 0.201$), and 4.9% of the variance in the availability of AI inputs and feed (adjusted $R^2 = 0.033$) (Table 9). The effect of input availability on farmer knowledge was moderate ($f^2 = 0.291$), while the effect of farmer knowledge on cattle productivity was large ($f^2 = 0.372$) under the thresholds applied in the source analysis (Table 10).

Table 9. Coefficients of determination

Endogenous construct	R²	Adjusted R²
AI inputs and feed	0.049	0.033
Farmer knowledge	0.228	0.201
Cattle productivity	0.377	0.344

Source: Primary data (2026).

Table 10. Effect-size (f²) matrix

Predictor	AI inputs and feed	Farmer knowledge	Cattle productivity
Land tenure rights	0.051	0.035	0.000
AI inputs and feed	—	0.291	0.018
Farmer knowledge	—	—	0.372
Cattle productivity	—	—	—

Source: Primary data (2026).

The estimated direct paths and their significance tests are reported in Table 11. The corresponding bootstrapped t statistics are visualized in Figure 3.

Table 11. Path coefficients and significance tests

Structural path	β	Mean	SD	t	p
Land tenure rights → AI inputs and feed	0.221	0.154	0.250	0.884	0.188
Land tenure rights → farmer knowledge	−0.169	−0.148	0.160	1.057	0.145
Land tenure rights → cattle productivity	−0.015	−0.008	0.136	0.107	0.458
AI inputs and feed → farmer knowledge	0.486	0.485	0.121	4.012	<0.001
AI inputs and feed → cattle productivity	0.125	0.118	0.154	0.811	0.209
Farmer knowledge → cattle productivity	0.548	0.558	0.120	4.550	<0.001

Source: Primary data (2026).

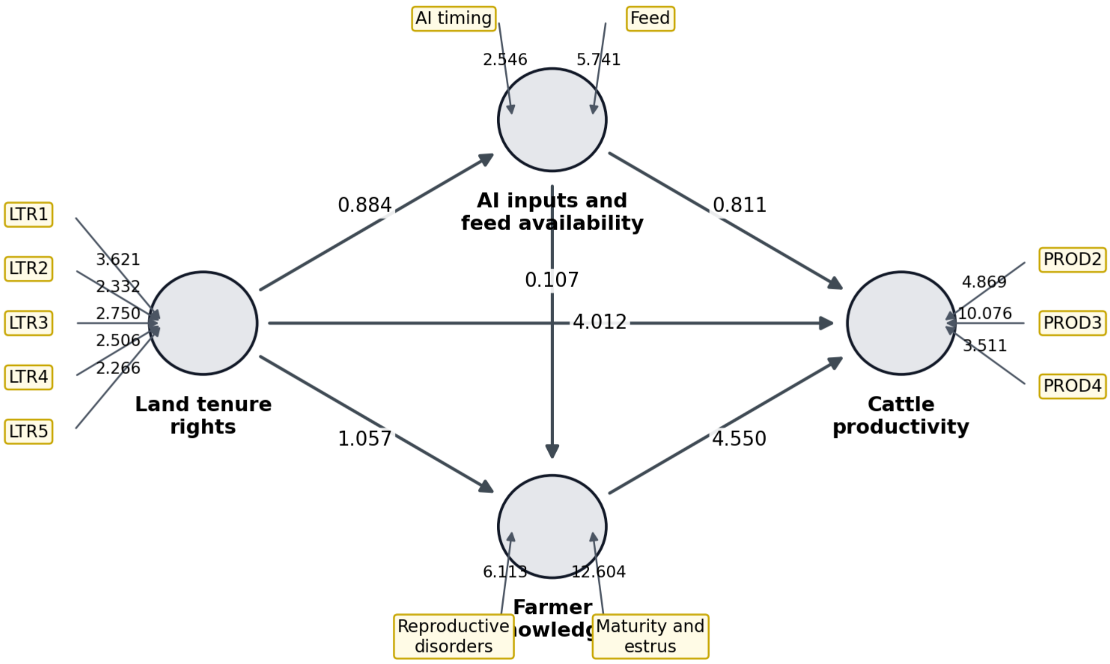

Figure 3. PLS-SEM inner model showing t statistics.

Only two of the six hypothesized structural relationships were significant (Table 11). The availability of AI inputs and feed had a positive association with farmer knowledge ($\beta = 0.486$, $t = 4.012$, $p < 0.001$), and farmer knowledge had a positive association with cattle productivity ($\beta = 0.548$, $t = 4.550$, $p < 0.001$). Land tenure rights were not significantly associated with input availability, farmer knowledge, or cattle productivity. The direct path from AI-input and feed availability to cattle productivity was also not significant ($\beta = 0.125$, $t = 0.811$, $p = 0.209$).

DISCUSSION

The respondent profile shows that UPSUS SIWAB in Lolong Guba operates mainly within experienced, smallholder farming households whose formal education is limited and whose livelihoods combine crop and livestock activities. Long farming experience can support practical husbandry knowledge, but limited schooling may constrain access to written technical information or unfamiliar reproductive technologies. Extension materials should therefore emphasize demonstrations, local-language explanation, repeated practice, and visual guidance. This approach is consistent with the need to integrate breeding technology with farmer-centered management support [1,10].

The strongest program pathway identified in the model ran from the availability of AI inputs and feed to farmer knowledge and subsequently to cattle productivity. Timely access to insemination services and feed appears to create opportunities for farmers to interact with field personnel, observe reproductive events, and apply advice on estrus, maturity, and reproductive disorders. The positive input-to-knowledge relationship is consistent with studies of AI adoption and UPSUS SIWAB implementation, which emphasize that technology availability must be accompanied by farmer uptake and operational support [5–8]. It also reinforces the importance of reliable forage strategies and locally available feed resources [2,3].

Farmer knowledge had the largest significant direct association with cattle productivity. This result suggests that recognizing estrus, understanding breeding age, and responding appropriately to reproductive disorders are central mechanisms through which program resources are converted into productive outcomes. Practical knowledge can reduce missed breeding opportunities, improve the timing of insemination, and prompt earlier contact with animal-health or insemination personnel. These mechanisms align with technical guidance on cattle mating management and research on AI success [1,11].

The direct association between AI-input and feed availability and productivity was positive but not significant. A plausible interpretation is that inputs alone do not guarantee improved outcomes; they become effective when farmers know when and how to use them and when services are delivered at the correct reproductive stage. Similarly, land tenure rights did not significantly predict input access or productivity. In the study area, AI facilities and services were largely delivered through government-supported field programs, so access was not determined primarily by farm landholdings. Program design should therefore avoid using land area as the principal targeting criterion and should instead prioritize reproductive readiness, service coverage, feed continuity, and participation in extension activities.

The model has practical implications for UPSUS SIWAB management. First, inseminators and extension officers should coordinate input delivery with short, repeated learning sessions on heat detection, breeding records, reproductive disorders, and feed management. Second, service units should maintain functional AI containers and dependable supply chains at the regency depot. Third, simple monitoring indicators should link the date of farmer reporting, insemination, pregnancy checking, calving, and follow-up education. Such integration may strengthen the economic value of the program because productivity gains are more likely when technology, feed, and knowledge are delivered as a coherent package [9].

Several limitations require caution. The study involved 60 respondents in one district and used a cross-sectional, nonexperimental design; the estimated paths therefore do not establish causality or represent all cattle farmers in Buru Regency. Some constructs had low or negative Cronbach's alpha despite acceptable composite reliability and AVE, suggesting possible indicator-coding or internal-consistency problems that should be re-examined in future instrument development. The highest VIF values also indicate potential collinearity among land-tenure indicators. Future research should use a larger probability sample, verify measurement scales before field deployment, report the software and bootstrapping settings in full, and include direct household-income indicators if the economic consequences of UPSUS SIWAB are to be evaluated.

CONCLUSION

UPSUS SIWAB participants in Lolong Guba were predominantly experienced smallholders with limited formal education and diversified livelihoods centered on crop and cattle farming. The model explained 37.7% of the variance in cattle productivity. The availability of artificial-insemination inputs and feed was positively associated with farmer knowledge, and farmer knowledge was positively associated with cattle productivity; the remaining structural paths were not significant. These results indicate that input provision should not be treated as a stand-alone intervention. Program managers should combine reliable AI and feed services with practical education on estrus detection, sexual maturity, reproductive disorders, breeding records, and follow-up care. Because the evidence is cross-sectional and some measurement-consistency indicators were weak, the findings should be confirmed with a larger sample and a strengthened instrument before broad causal or economic conclusions are drawn.

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