

Article

Socioeconomic Determinants of Sustainable Technology Adoption and Its Influence on Brazilian Agricultural GVP

Diego Pierotti Procópio ^{1,*}, Matheus Wemerson Gomes Pereira ², Renato Luiz Sproesser ³
and Elaine Aparecida Fernandes ⁴

¹ Department of Animal Science and Rural Extension (DZER) and Graduate Program in Economics, Universidade Federal de Mato Grosso (UFMT), Cuiabá 78060-900, MT, Brazil

² School of Administration and Business (ESAN) and Graduate Program in Business Administration, Universidade Federal de Mato Grosso do Sul (UFMS), Campo Grande 79070-900, MS, Brazil; matheus.pereira@ufms.br

³ School of Administration and Business (ESAN), Universidade Federal de Mato Grosso do Sul (UFMS), Campo Grande 79070-900, MS, Brazil; renato.sproesser@gmail.com

⁴ Department of Economics (DEE) and Graduate Program in Economics, Universidade Federal de Viçosa (UFV), Viçosa 36570-900, MG, Brazil; eafernandes@ufv.br

* Correspondence: diego.procopio@ufmt.br

Abstract

Brazil's agricultural sector is characterized by persistent productive duality: a technologically advanced export-oriented segment coexists with a large stratum of smallholders generating low economic returns. Understanding the economic determinants of this gap requires moving beyond individual farm surveys toward systemic, nationally representative evidence. This study examines the socioeconomic drivers of sustainable technology adoption and their effect on the Gross Value of Production (GVP) in Brazilian agriculture, using data from the 2017 Agricultural Census aggregated to 558 micro-regions and Partial Least Squares Structural Equation Modeling (PLS-SEM). Unlike prior survey-based studies, the census-based approach reduces sample selection bias relative to small-sample surveys and supports a macro-level, ecological analysis grounded in complete census coverage. The structural model explains 69.2% of the variance in technology adoption ($R^2_{adj} = 0.692$) and 47.4% of the variance in GVP ($R^2_{adj} = 0.474$). The results show that rural cooperatives are the dominant institutional mechanism driving both credit access ($\beta = 0.733$) and technical assistance ($\beta = 0.746$), with effect sizes far exceeding those of individual-level factors. Access to technical information ($\beta = 0.215$) and technology adoption itself ($\beta = 0.179$) also positively influence GVP. These findings indicate that overcoming productive duality requires a systemic policy approach centered on rural cooperativism, digital connectivity, and institutional capacity.

Keywords: sustainable agriculture; technology adoption; PLS-SEM; productive duality; census data; collective organizations; Brazil

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1. Introduction

Climate change threatens food production by raising global temperatures and increasing levels of atmospheric CO₂—one of the main greenhouse gases. These changes trigger extreme weather events, including droughts, heavy rainfall, heatwaves, cold snaps, and shifts in precipitation patterns (Malhi et al., 2021). Such temperature variations reduce

agricultural productivity across various countries, affecting staple crops like cotton, rice, barley, sugarcane, sunflower, cassava, maize, soybean, and sorghum.

Technological intensification in agriculture primarily aims to increase productivity and enhance food output. However, these strategies often harm soil health. Consequences include declines in soil organic matter and biological diversity, increased erosion and physical degradation, reduced nutrient-use efficiency, groundwater pollution, and higher greenhouse gas (GHG) emissions (Kopittke et al., 2019; Kabato et al., 2025). Soil degradation essentially involves the loss of biological, physical, and chemical characteristics necessary for plant development (Gao et al., 2024).

Adopting sustainable technologies is essential for building resilience against climate variability, raising productivity, and conserving natural resources such as water, biodiversity, and soil (Ogwu & Kosoe, 2025). Agricultural sustainability, in this sense, rests on redesigning production systems to integrate ecological processes—nutrient cycling, pest regulation, and soil-forming processes—into farm management while making productive use of farmers' collective knowledge and capacities (Pretty, 2008). Evidence from sustainable-intensification programs elsewhere in the developing world shows that such integration can raise yields and resource-use efficiency at scale when supported by appropriate institutions and knowledge-sharing networks (Pretty et al., 2011). Key technologies that contribute to soil conservation include crop rotation, no-till systems, and the use of inputs, correctives, and fertilizers (Manda et al., 2016; Topa et al., 2025). Despite their importance, adoption rates in Brazil remain low. According to the 2017 Agricultural Census, out of 5.07 million rural properties nationwide, only 946,600 used crop rotation (18.66%), 553,380 used no-till systems (10.91%), 2.14 million used fertilizers (42.27%), and 728,540 used soil correctives (14.36%) (IBGE, 2019).

Technology adoption in agriculture is a complex process shaped by environmental, cultural, economic, institutional, political, and social factors. These can be grouped into three categories: (a) characteristics of the socio-economic environment where the farm is located, (b) farm characteristics, and (c) farmer characteristics (Munguia & Llewellyn, 2020; Procópio et al., 2024; Procópio, 2024). This process is consistent with diffusion-of-innovations theory, which frames adoption as a sequential, socially embedded learning process rather than a single binary decision (Rogers, 2003). At the systemic level, the innovation-systems perspective further emphasizes that adoption outcomes depend not only on individual farm attributes but also on the density and quality of institutional linkages—extension services, cooperatives, credit providers, and research organizations—that structure the flow of knowledge and resources to producers (Spielman & Birner, 2008). Empirical evidence from other developing-country contexts corroborates this systemic view: extension access and cooperative membership have been shown to jointly enhance technology adoption and household welfare, with effects that are amplified when combined with formal credit access (Wossen et al., 2017).

Brazilian agriculture exhibits a persistent duality. On one hand, a group of highly technical and specialized agents produces food and raw materials for processing industries and domestic and international markets. On the other, a large segment of rural producers lives in socioeconomic vulnerability, producing mainly for family subsistence. These producers need financial resources, land access, and appropriate technologies to increase their productivity and output (Pereira et al., 2024).

The 2017 Census illustrates this gap. Most rural properties had low agricultural productivity: approximately 3.73 million establishments (73.98% of the total) generated an annual Gross Value of Production (GVP) of up to BRL 25,000 (about US\$ 7837) (IBGE, 2019). Despite the potential of sustainable technologies to mitigate climate impacts and improve

economic outcomes, the complex interplay among socioeconomic drivers, technology adoption, and GVP remains underexplored in Brazil (Procópio, 2024; Tanure et al., 2024).

This study examines the socioeconomic determinants of sustainable technology adoption and analyzes their influence on GVP in the Brazilian agricultural sector. Structural Equation Modeling (SEM) is employed to analyze the interactions among farm-level characteristics, technological choices, and economic performance, thereby uncovering the structural barriers that perpetuate productive duality. Unlike prior farm-level surveys with limited geographic scope, this research draws on national census data aggregated to 558 micro-regions, providing a macro-level, ecological analysis grounded in complete national census coverage of the determinants of adoption and their economic consequences.

2. Materials and Methods

2.1. Study Area and Data Source

The data for this study were obtained from the 2017 Agricultural Census, conducted by the Brazilian Institute of Geography and Statistics (IBGE). This census represents the official survey of the Brazilian agricultural sector, collecting data on land use, the technological patterns of production systems, and the socioeconomic conditions of rural producers. The unit of analysis was the Brazilian micro-region, comprising 558 units.

2.2. Theoretical Model and Hypotheses

Properly understanding the technology adoption process in the agricultural sector requires moving beyond the traditional binary decision framework (adopt or not adopt) and treating the phenomenon as a dynamic, multi-stage learning process. A central premise is that farmers are motivated to improve their current situation, which could be driven by economic factors (increasing productivity and profit, for example) or be related to the family's living conditions (incorporating labor-saving technologies so that the producer has more time to spend with family members). Moreover, it must be recognized that producers have limited resources (time, money, information, and cognitive capacity) and cannot immediately determine which technologies offer the greatest relative advantages for achieving their personal goals (Weersink & Fulton, 2020).

Adopting technology in the agricultural sector generally involves a social process, as farmers seek information from networks of contacts (trade associations, cooperatives, associations, extension companies, other farmers, etc.) or operate as part of a family team that manages the farm. When a decision on technology adoption is very complex, the producer's decision-making process tends to be a shared social endeavor (Pannell et al., 2006).

The adoption of technology in the agricultural sector is positively influenced by access to credit (H1) and technical assistance (H2) (Ruzzante et al., 2021). The participation of rural producers in collective action entities facilitates the exchange and acquisition of technical information on and experience in the use of technologies in agricultural production systems, thereby contributing to technology adoption (H3) (Zhang et al., 2020). It also facilitates access to technical assistance services (H4) and credit (H5) (Markelova et al., 2009).

Water availability on rural properties contributes to the adoption of technology in the rural sector (H6) (Kharel et al., 2023). The presence of productive machinery and equipment (H7) (Jones-Garcia & Krishna, 2021), as well as sources of technical information (newspapers, magazines, and devices with internet connection) (H8) (Giua et al., 2021), also exerts a positive influence on the technology adoption process in the agricultural sector.

Higher levels of education among rural producers positively influence the adoption of agricultural technologies (H9) (Paltasingh & Goyari, 2018). Farmer age is negatively associated with technology adoption in the rural sector (H10). Older rural producers may exhibit less energy, have a shorter planning horizon (compared to younger individuals), and

show greater resistance to changes needed in the production system when implementing new technology (Souza Filho et al., 2011).

Beyond the determinants of adoption, the structural model assesses the factors driving economic performance. First, the adoption of technology is hypothesized to exert a significant positive influence on GVP (H11), as technological intensification optimizes resource use and increases agricultural output (Geng et al., 2024). Similarly, the participation of rural producers in collective action organizations—such as cooperatives and associations—is expected to positively impact GVP (H12) by strengthening bargaining power, reducing transaction costs, and improving market positioning (Mutonyi, 2019).

Furthermore, access to technical assistance services is considered a crucial driver of economic success, positively influencing GVP by professionalizing farm management and precisely applying productive inputs (H13) (Danso-Abbeam et al., 2018). Finally, access to diverse sources of technical information also positively influences GVP (H14) by reducing information asymmetry and enabling producers to adopt more efficient, data-driven production strategies (Nikam et al., 2022). The relationships among the hypotheses are presented in Table 1 and Figure 1.

Table 1. Hypotheses of the theoretical model.

Hypothesis	Description	Expected Relationship
Influence on the technology adoption construct		
H1	Access to credit positively influences the adoption of sustainable technologies.	Positive
H2	Access to technical assistance positively influences the adoption of sustainable technologies.	Positive
H3	The participation of rural producers in collective organizations positively influences the adoption of sustainable technologies.	Positive
H6	The availability of water on farms has a positive influence on the adoption of sustainable technologies.	Positive
H7	The availability of productive machinery and equipment on farms positively influences the adoption of sustainable technologies.	Positive
H8	The availability of technical information sources on farms positively influences the adoption of sustainable technologies.	Positive
H9	Higher levels of education among rural producers positively influence the adoption of sustainable technologies.	Positive
H10	The older age group of rural producers has a negative influence on the adoption of sustainable technologies.	Negative
Influence on the constructs of access to technical assistance services and credit		
H4	Rural producers' participation in collective organizations positively influences access to credit.	Positive
H5	Rural producers' participation in collective organizations positively influences access to technical assistance.	Positive
Influence on the GVP construct		
H11	The adoption of sustainable technologies positively influences the GVP.	Positive
H12	The participation of rural producers in collective organizations positively affects GVP.	Positive
H13	Access to technical assistance positively influences the GVP.	Positive
H14	Access to technical information sources positively affects the GVP.	Positive

Source: the authors (2026). Note on H10: the age construct was initially specified with indicators spanning the full age distribution of rural producers. During measurement-model refinement (Section 2.3), only the three youngest age brackets (under 45 years) met the retention criteria; the three oldest brackets did not. As a result, the retained AF construct empirically measures the share of younger producers, and its structural path is positive ($\beta = 0.113, p < 0.01$). Because the retained brackets are the complement of the originally hypothesized older-age population, this positive coefficient is consistent with—not a contradiction of—the negative relationship with older age proposed in H10 and in the literature (Souza Filho et al., 2011); see Section 4.1 for the full explanation.

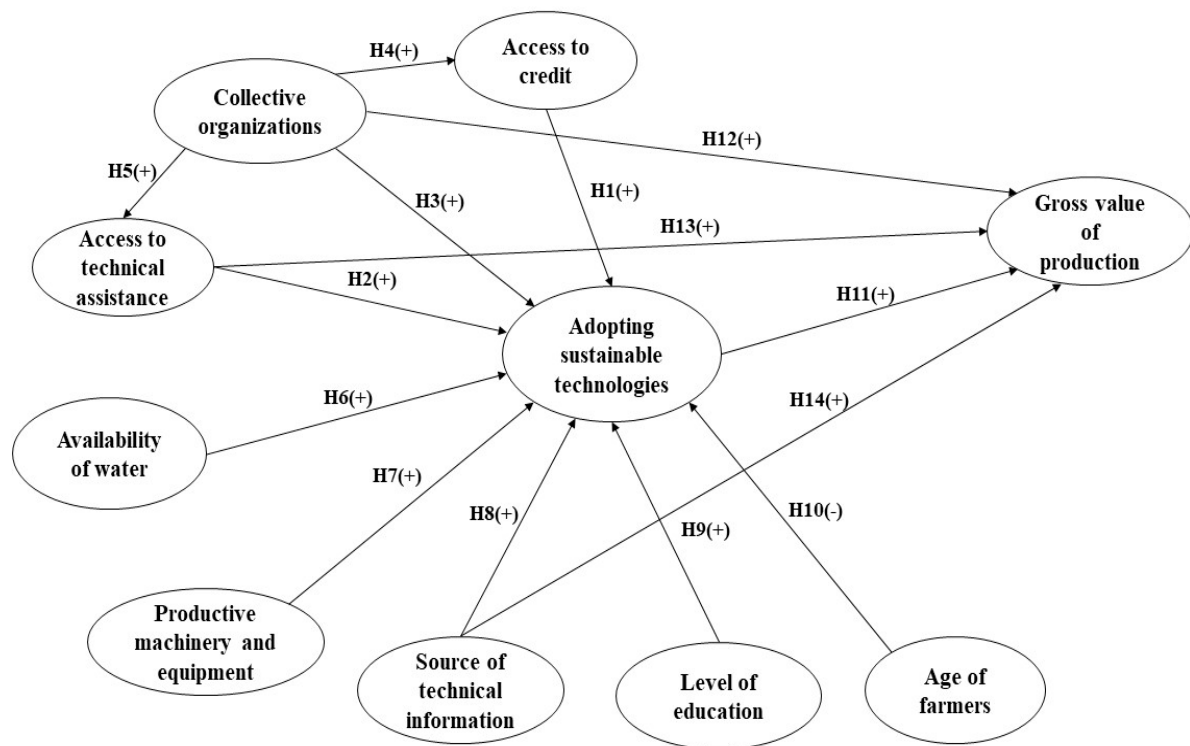


Figure 1. Proposed theoretical model and research hypotheses. Source: the authors (2026).

2.3. Technical Data Analysis

Data were analyzed using Structural Equation Modeling (SEM), a multivariate statistical technique that describes the relationships among constructs—latent variables measured through multiple indicators (Hair et al., 2017; Quevedo-Silva & Pereira, 2022). This study employs Partial Least Squares (PLS-SEM), an approach where a series of least-squares regressions estimates the model parameters. PLS-SEM involves the assessment of two models: the measurement model (outer model), which evaluates the relationships between constructs and their indicators (observable variables), and the structural model (inner model), which assesses the relationships among the constructs themselves to validate the theoretical hypotheses (Nascimento & Macedo, 2016).

Initially, 42 observable variables were selected from the 2017 Agricultural Census to represent the constructs in the theoretical framework (Figure 1). To ensure comparability, these variables were normalized by the total number of properties (NP), the total area of properties (AP), or the total personnel employed (PE) (Gomes et al., 2024).

The choice of denominator follows the nature of the raw census count for each indicator (e.g., counts of establishments using a given input are normalized by NP, while counts tied to farmed area or hired labor are normalized by AP or PE, respectively), and indicators within the same construct generally share a denominator by design, since they describe the same underlying unit of observation; this is a modeling choice made for conceptual consistency within each construct rather than a source of purely mechanical correlation, though we acknowledge that shared denominators can inflate within-construct correlations to some degree, which is a further reason to prioritize robustness checks using alternative normalizations and raw counts with appropriate controls for micro-region size.

Rate-based normalization of this kind—expressing establishment counts relative to the number of properties, area, or personnel in each micro-region—follows the same denominator logic previously employed for census-based agricultural indicators in Brazil (Gomes et al., 2024) and mirrors the approach used in other agricultural-census-based regional studies—for example, Xavier et al. (2022), who normalize Portuguese municipal-level

agricultural census indicators by number of farms and by hectare of utilized agricultural area for the same reason: raw counts are not directly comparable across regions of very different size.

We have not, however, formally re-estimated the structural model using an alternative normalization base (e.g., raw counts with micro-region-size controls) to confirm that path coefficients are unaffected by this specific choice; this remains an open robustness check, which we flag explicitly in the Limitations (Section 5) rather than assume it is not relevant.

All statistical procedures were performed using SmartPLS® 3 software (SmartPLS GmbH, Bönningstedt, Germany).

Variable selection began with all census indicators conceptually linked to each construct in the theoretical framework (Figure 1); indicators were retained in the initial 42-variable model when they had a plausible theoretical link to their target construct and adequate cross-micro-region variability. Indicators were subsequently removed from the measurement model when their standardized outer loading fell below 0.40 or when their retention deteriorated the AVE or CR of the corresponding construct below the 0.50/0.70 thresholds (Hair et al., 2017); indicators with loadings between 0.40 and 0.70 were retained when their removal did not improve AVE/CR, following the recommendation that loadings in this intermediate range be evaluated by their impact on convergent validity rather than dropped automatically.

The AST construct combines fertilizer use with crop rotation, no-till systems, and soil correctives. Fertilizer use alone is not inherently a sustainable practice, since its environmental performance depends on type, application rate, timing, and agronomic context that the census does not capture. In this model, fertilizer use is retained as an AST indicator because, in combination with the other three indicators—each of which is unambiguously a conservation practice—it serves as a proxy for a broader pattern of technified, input-intensive management that typically co-occurs with conservation adoption in the Brazilian context; it should therefore be read as part of a composite indicator of technological intensification with a conservation orientation, rather than as an independent claim that fertilizer application is itself environmentally sustainable.

Regarding model specification, most constructs in this study (AST, ATA, AC, STI, CO, GVP) are treated as reflective, consistent with the assumption that their indicators are interchangeable manifestations of an underlying latent trait and are expected to co-vary, which the acceptable AVE and CR values in Table 2 support. Three constructs—PME (machinery and equipment), AW (water sources), and AF (age brackets)—combine indicators that could plausibly be specified as formative, since each indicator captures a distinct type of asset or age bracket rather than a strictly interchangeable manifestation of the same trait. These constructs were nonetheless evaluated using reflective criteria (loadings, AVE, CR) for consistency with the rest of the measurement model and because their indicators are conceptually correlated (e.g., ownership of one type of machinery is associated with ownership of others in more capitalized establishments), and they achieved acceptable reflective fit statistics (Table 2). We acknowledge this as a modeling simplification; a formative respecification of these three constructs is a direction for future refinement of the model.

Full definitions, denominators, and elimination status for the 42 initial observable variables are provided in Table A1 below, together with the normalization formulas and indicator-elimination criteria described in Section 2.3. In place of individual IBGE SIDRA table/cell identifiers, we provide complete variable definitions and formulas, which we consider sufficient for independent replication from the publicly available 2017 Agricultural Census microdata; the underlying census query parameters are available from the corresponding author upon direct request.

Table 2. Correlation matrix between latent variables.

	AC	ATA	AST	AW	STI	AF	PME	LE	CO	GVP
AC	0.740									
ATA	0.610	0.795								
AST	0.653	0.695	0.787							
AW	0.319	0.328	0.458	0.708						
STI	0.325	0.627	0.626	0.405	0.747					
AF	−0.222	−0.319	−0.283	−0.221	−0.429	0.807				
PME	0.603	0.637	0.689	0.449	0.560	−0.407	0.919			
LE	0.351	0.427	0.550	0.523	0.528	−0.461	0.525	0.736		
CO	0.733	0.746	0.743	0.416	0.574	−0.361	0.799	0.478	0.903	
GVP	0.436	0.607	0.606	0.375	0.569	−0.349	0.704	0.427	0.615	0.837
AVE	0.547	0.633	0.620	0.502	0.557	0.652	0.844	0.542	0.815	0.701
CR	0.774	0.771	0.867	0.732	0.787	0.848	0.942	0.771	0.898	0.823

Source: research results. Note: AVE—Average Variance Extracted; CR—Composite Reliability. Constructs: AC—access to credit; ATA—access to technical assistance; AST—adopting sustainable technologies; AW—availability of water; STI—sources of technical information; AF—age of farmers; PME—productive machinery and equipment; LE—level of education; CO—collective organizations; GVP—Gross Value of Production. Diagonal values (the row–column intersection of each construct with itself) report the square root of the AVE for that construct, per the Fornell–Larcker criterion; off-diagonal values are inter-construct correlations. Given that some inter-construct correlations approach their corresponding $\sqrt{\text{AVE}}$ values (e.g., ATA–CO at 0.746 against $\sqrt{\text{AVE}}$ of 0.795 and 0.903, respectively), a Heterotrait–Monotrait (HTMT) ratio analysis was conducted as an additional, more conservative discriminant-validity check (Appendix A, Table A2).

In accordance with journal policy on generative artificial intelligence (GenAI), we disclose that a GenAI large language model (Claude Sonnet 5, Anthropic, San Francisco, CA, USA) was used during the preparation of this manuscript for textual adjustment and structural organization of the article. The authors have reviewed and edited all GenAI-assisted output and take full responsibility for the content of this publication.

3. Results

3.1. Measurement Model

The first stage of the SEM involves validating the measurement model through convergent validity, discriminant validity, and Composite Reliability. Convergent validity was assessed using the Average Variance Extracted (AVE), with a cutoff value of 0.50. Discriminant validity, which ensures the distinction of a construct from others, was evaluated using cross-loadings and the Fornell and Larcker (1981) criterion. According to this criterion, the square root of the AVE for each latent variable must be greater than its correlations with all other constructs in the model. Furthermore, Composite Reliability (CR) for the constructs was used to assess sample bias and was required to be greater than 0.70 (Hair et al., 2017).

The initial model, comprising 42 observable variables, did not initially meet all measurement model criteria. Consequently, iterative adjustments were made to the measurement model until it achieved adequate fit ($\text{AVE} > 0.50$; $\text{CR} > 0.70$) (Table 2). This was accomplished by removing low-loading indicators and applying a logarithmic transformation to the GVP indicator. The logarithmic transformation is essential for reducing skewness in the data distribution and improving the model's predictive properties (Fávero et al., 2014).

The HTMT results (Appendix A, Table A2) reveal a substantial discriminant-validity concern that qualifies the interpretation of several structural paths. Using the conservative $\text{HTMT} \leq 0.85$ threshold (Henseler et al., 2015), 13 of the 45 construct pairs (29%) exceed

this threshold, and six pairs—ATA–AC, ATA–AST, CO–AC, CO–ATA, GVP–ATA, and STI–ATA—exceed 1.00, indicating that these construct pairs are not clearly distinguishable on the basis of the available indicators. The violations concentrate heavily around ATA and CO, the two constructs retained with only two indicators each (ATA2/ATA3 and CO1/CO4, respectively) after measurement-model refinement; two-indicator reflective constructs are known to produce less stable, and often inflated, HTMT estimates in PLS-SEM. Substantively, ATA’s poor discriminability from AC, AST, CO, GVP, and STI, and CO’s poor discriminability from AC and PME, are consistent with this study’s central empirical narrative that rural cooperatives channel credit, technical assistance, and collective action through the same institutional structure (Section 4.3); statistically, however, this makes it difficult to attribute fully independent, uniquely identified effects to AC, ATA, and CO individually. We report this result transparently rather than omit it: the path coefficients for AC, ATA, and CO should be interpreted as capturing a broader dimension of institutional support channeled substantially through cooperatives, rather than as fully separable constructs, and we flag this as a priority for future model refinement—for example, re-specifying AC, ATA, and CO as reflective indicators of a single higher-order “institutional support” construct, or enriching the ATA and CO measurement blocks with additional census indicators to stabilize their estimates.

Table 3 presents information on the adjusted measurement model, including the observable variables and their corresponding factor loadings (ranging from 0.379 to 0.938).

To support discriminant validity, the factor loadings for the observed variables should exceed 0.70 (Hair et al., 2017). The variables AC3 (0.473), ATA2 (0.658), AW3 (0.379), STI2 (0.582), and LE1 (0.479) had factor loadings below 0.70. However, maintaining the largest possible number of indicators in the measurement model is advisable to avoid compromising the content validity of the constructs (Bido & Silva, 2019). In exploratory PLS-SEM models, Hair et al. (2017, p. 115) acknowledge that loadings between 0.40 and 0.70 may be retained when their removal would reduce AVE or CR below acceptable thresholds, or when the indicator captures theoretically relevant content not represented by other items in the construct.

A related specification concern is that ATA3 and CO1 are both drawn from census counts of cooperatives per property (cooperatives/np) but load on different constructs—ATA (access to technical assistance) and CO (collective organizations), respectively. This reflects two conceptually distinct roles that cooperatives play in the theoretical model rather than a duplicated measure: ATA3 captures cooperatives as a channel through which producers access technical assistance, whereas CO1 captures cooperative membership/participation itself as a form of collective organization. Discriminant validity between ATA and CO was nonetheless confirmed by the Fornell–Larcker criterion (Table 2), where the square root of the AVE for each construct exceeds their cross-construct correlation (0.746), supporting their treatment as distinct latent variables despite drawing on related census items.

One indicator, AW3 (artesian wells), falls below even the 0.40–0.70 exploratory range at 0.379. Its retention is justified primarily on content-validity grounds rather than statistical grounds alone: content validity concerns whether a construct’s indicator set adequately represents the full conceptual domain it is meant to measure (Nunnally & Bernstein, 1994), which is a criterion distinct from—and not fully substitutable by—the convergent-validity statistics (loadings, AVE, CR) used elsewhere in the measurement model. Water availability, as a construct, spans structurally distinct sources with different reliability, seasonality, and infrastructure requirements; artesian wells (AW3) capture a source qualitatively different from surface springs (AW1) and rivers/streams (AW2), namely groundwater accessed through fixed infrastructure rather than surface collection. Removing AW3 would leave

the construct representing only surface-water sources, narrowing its content coverage and threatening construct validity even though doing so would mechanically raise the average loading. The full measurement-model assessment was re-run with AW3 included, and the AW construct meets the AVE (0.502) and CR (0.732) thresholds under this specification (Table 2), supporting its retention on both content and (minimally sufficient) statistical grounds.

Table 3. Observable variables of the adjusted measurement model.

Constructs	Observable Variables	Factor Loadings
AST—Adopting sustainable technologies	AST1—Fertilizers/np	0.823
	AST2—Crop rotation/np	0.785
	AST3—Soil Correctives/pe	0.774
	AST4—No-till system/np	0.765
AC—Access to credit	AC1—Banks (also includes financial resources from rural credit lines)/np	0.821
	AC2—Credit cooperatives/np	0.862
	AC3—Governments (federal, state, and municipal)/np	0.473
ATA—Access to technical assistance	ATA2—Rural producer (or contractor)/ap	0.668
	ATA3—Cooperatives/np	0.905
CO—Collective organizations	CO1—Cooperatives/np	0.919
	CO4—Technical meetings and seminars/np	0.886
AW—Availability of water	AW1—Springs/np	0.911
	AW2—Rivers/streams/np	0.729
	AW3—Artesian wells/np	0.379
PME—Productive machinery and equipment	PME1—Tractors/np	0.889
	PME2—Seeders/planters/np	0.928
	PME3—Fertilizer spreaders, harvesters, or lime spreaders/np	0.938
STI—Sources of technical information	STI1—Magazines/ap	0.856
	STI2—Newspapers/ap	0.582
	STI5—Devices with internet connection/np	0.775
LE—Level of education	LE1—Higher education/pe	0.479
	LE5—Former high school (1st cycle)/np	0.819
	LE6—Former primary school (elementary)/np	0.851
AF—Age of farmers	AF1—Under 25 years old/np	0.867
	AF2—From 25 to under 35 years old/np	0.836
	AF3—From 35 to under 45 years old/np	0.710
GVP—Gross Value of Production	GVP2—Gross Value of Production divided by the area of properties (ap)	0.905
	lgvp1—Logarithm of GVP1/np	0.764

Source: research results. Note: np—number of properties; ap—total area of properties; pe—total personnel employed.

We nonetheless flag AW3 as the weakest indicator in the model. As a robustness check, the structural model was re-estimated with AW3 excluded (AW measured by AW1 and AW2 only). All 14 structural path coefficients remained within 0.009 of their original values, and $AW \rightarrow AST$, far from being driven by AW3, was slightly stronger and more precisely estimated without it ($\beta = 0.066$ vs. 0.057 ; $p = 0.022$ vs. 0.048). Discriminant validity

for AW also improved: the LE–AW HTMT ratio dropped from 0.933 to 0.842, resolving that violation, while the six HTMT violations exceeding 1.00 (all involving ATA or CO) were unaffected, confirming they are unrelated to AW3 and specific to the thin ATA/CO measurement blocks discussed above.

3.2. Structural Model

The structural model was evaluated using Pearson’s coefficients of determination, multicollinearity analysis, f^2 effect size, and the significance of the coefficients (Ringle et al., 2014; Bido & Silva, 2019) (Table 4). R^2 measures the proportion of the variance in the endogenous latent variables (AST, AC, ATA, and GVP) explained by the structural model (Ringle et al., 2014). The adjusted R^2 accounts for model complexity and sample size and ranges from 0 to 1 (Henseler et al., 2016).

The model explained 69.20% (0.692) of the variance in the adoption of sustainable technologies (AST) in the Brazilian agricultural sector. In the constructs of access to technical assistance services (ATA) and credit (AC), the adjusted R^2 values were 55.60% (0.556) and 53.60% (0.536), respectively. For the GVP construct, the adjusted R^2 for GVP was 47.40% (0.474) (Table 4).

Collinearity was assessed using variance inflation factors (VIFs) for the latent variables. In the PLS-SEM approach, a VIF value below 5.00—equivalently, a tolerance ($1/\text{VIF}$) above 0.20—is used as the threshold to avoid collinearity in the model (Hair et al., 2017). For all causal relationships (H1 to H14), the VIF value was within the recommended range (Table 4).

Table 4. Results of the structural model.

Relationships	Hypotheses	VIF	f^2	β	SE	Sig. (p -Value) [95% CI]	R^2	Adj. R^2 (Q^2)
AC → AST	H1	2.371	0.083	0.245	0.038	<0.001 [95% CI: 0.171; 0.319]	0.696	0.692 ($Q^2 = 0.417$)
ATA → AST	H2	2.756	0.027	0.151	0.049	0.002 *** [95% CI: 0.055; 0.247]		
AW → AST	H6	1.502	0.007	0.057	0.029	0.048 ** [95% CI: 0.000; 0.114]		
STI → AST	H8	2.185	0.082	0.233	0.039	<0.001 [95% CI: 0.157; 0.309]		
AF → AST	H10	1.396	0.030	0.113	0.026	<0.001 [95% CI: 0.062; 0.164]		
PME → AST	H7	3.123	0.017	0.126	0.047	0.008 *** [95% CI: 0.034; 0.218]		
LE → AST	H9	1.890	0.043	0.157	0.037	<0.001 [95% CI: 0.084; 0.230]		
CO → AST	H3	4.667	0.018	0.160	0.057	0.005 *** [95% CI: 0.048; 0.272]		
ATA → GVP	H13	2.723	0.023	0.182	0.066	0.006 *** [95% CI: 0.051; 0.313]	0.478	0.474 ($Q^2 = 0.317$)
AST → GVP	H11	2.697	0.023	0.179	0.053	0.001 *** [95% CI: 0.075; 0.283]		
STI → GVP	H14	1.870	0.047	0.215	0.049	<0.001 [95% CI: 0.119; 0.311]		
CO → GVP	H12	2.903	0.033	0.223	0.060	<0.001 [95% CI: 0.105; 0.341]		
CO → AC	H4	1.000	1.161	0.733	0.027	<0.001 [95% CI: 0.680; 0.786]	0.537	0.536 ($Q^2 = 0.283$)
CO → ATA	H5	1.000	1.256	0.746	0.026	<0.001 [95% CI: 0.695; 0.797]	0.557	0.556 ($Q^2 = 0.329$)

Source: research results. Note: *** 1% significance level; ** 5% significance level. Constructs: AC—access to credit; ATA—access to technical assistance; AST—adopting sustainable technologies; AW—availability of water; STI—sources of technical information; AF—age of farmers; PME—productive machinery and equipment; LE—level of education; CO—collective organizations; GVP—Gross Value of Production. p -values were obtained using bootstrapping with 5000 repetitions, and 95% confidence intervals were computed as $\beta \pm 1.96 \times \text{SE}$ from the same bootstrap run (normal approximation); none of the 14 structural paths’ intervals include zero, though the interval for AW → AST ([0.000; 0.114]) approaches zero at its lower bound, consistent with its p -value (0.048) being the closest to the 5% significance threshold. The Q^2 predictive-relevance values (blindfolding procedure, cross-validated redundancy) are reported in parentheses next to Adj. R^2 for the model’s four endogenous constructs: AST ($Q^2 = 0.417$), GVP ($Q^2 = 0.317$), AC ($Q^2 = 0.283$), and ATA ($Q^2 = 0.329$). All four values are well above zero, indicating medium-to-high predictive relevance (Hair et al., 2017); Q^2 is not applicable to the model’s purely exogenous constructs (AF, AW, CO, LE, PME, STI), which have no incoming structural paths.

4. Discussion

4.1. Robustness Check: Alternative Indicator Normalization

As requested during review, the structural model was re-estimated using an alternative, single-denominator normalization: all 27 retained observable variables were expressed relative to the number of properties (NP) in each micro-region, replacing the mixed NP/AP/PE scheme used in the main analysis for five indicators (AST3, ATA2, STI2, LE1, and GVP2). The model structure, indicator set, and estimation procedure (PLS-SEM, path weighting scheme, 5000-resample bootstrapping) were otherwise identical to the main analysis. Table 5 compares the two specifications.

Table 5. Structural path coefficients under the original (mixed NP/AP/PE) and alternative (NP-only) normalization schemes.

Relationship	Hyp.	β (Original NP/AP/PE)	Sig.	β (Alternative, NP Only)	Sig.	Status
AC $\rightarrow$ AST	H1	0.245	<0.001	+0.133	0.001	Robust
ATA $\rightarrow$ AST	H2	0.151	0.002	−0.019	0.708	Not robust
CO $\rightarrow$ AST	H3	0.160	0.005	+0.380	<0.001	Robust (strengthened)
AW $\rightarrow$ AST	H6	0.057	0.048	+0.092	0.002	Robust
PME $\rightarrow$ AST	H7	0.126	0.008	+0.323	<0.001	Robust (strengthened)
STI $\rightarrow$ AST	H8	0.233	<0.001	−0.048	0.312	Not robust
LE $\rightarrow$ AST	H9	0.157	<0.001	+0.141	<0.001	Robust
AF $\rightarrow$ AST	H10	0.113	<0.001	+0.058	0.054	Marginal
AST $\rightarrow$ GVP	H11	0.179	0.001	+0.112	0.035	Robust
CO $\rightarrow$ GVP	H12	0.223	<0.001	+0.053	0.422	Not robust
ATA $\rightarrow$ GVP	H13	0.182	0.006	+0.114	0.097	Not robust
STI $\rightarrow$ GVP	H14	0.215	<0.001	+0.379	<0.001	Robust (strengthened)
CO $\rightarrow$ AC	H4	0.733	<0.001	+0.732	<0.001	Robust
CO $\rightarrow$ ATA	H5	0.746	<0.001	+0.795	<0.001	Robust

Source: research results (SmartPLS 3 output, 5000-resample bootstrap for both specifications, $n = 558$). Values in red indicate paths that lose statistical significance ($\alpha = 0.05$) or change sign under the alternative normalization.

Nine of the fourteen structural paths remain statistically significant and in the same direction under the alternative normalization, including all paths originating from CO (collective organizations), which strengthen rather than weaken (CO $\rightarrow$ AST rises from $\beta = 0.160$ to 0.380; CO $\rightarrow$ AC and CO $\rightarrow$ ATA are essentially unchanged). AW $\rightarrow$ AST, LE $\rightarrow$ AST, AC $\rightarrow$ AST, AST $\rightarrow$ GVP, and STI $\rightarrow$ GVP also remain significant, the latter more than 50% larger under the alternative specification. However, five paths do not survive the alternative normalization: ATA $\rightarrow$ AST (H2) and ATA $\rightarrow$ GVP (H13) both lose significance and ATA $\rightarrow$ AST changes sign; CO $\rightarrow$ GVP (H12) loses significance; STI $\rightarrow$ AST (H8) loses significance and changes sign; and AF $\rightarrow$ AST (H10) falls just short of the 5% threshold ($p = 0.054$).

This pattern is not random with respect to the model's other diagnostics. The four paths that lose significance are precisely those originating from, or terminating in, the constructs already identified in the HTMT analysis (Section 3.1; Appendix A, Table A2) as having the weakest discriminant validity: ATA and CO show the most severe HTMT violations of any construct pair in the model, and STI's discriminant validity with ATA is likewise poor (HTMT = 1.180). When the shared variance among these overlapping

constructs is reshuffled by a change in indicator normalization, their individually estimated effects on AST and GVP shift accordingly—while CO's paths, drawing on a comparatively better-identified construct, absorb more of that variance and strengthen. We therefore treat the specific direct effects of ATA (H2, H13) and STI on AST (H8) as not robust to normalization choice, and interpret them with corresponding caution in Sections 4.2 and 4.4; the finding that collective organizations (CO) are the central institutional driver of adoption and GVP, and that STI's effect on GVP is robust, is reinforced rather than undermined by this check.

4.2. Determinants of Sustainable Technology Adoption

The structural model confirms that adoption of sustainable technologies (AST) in Brazilian agriculture is a multidimensional phenomenon. The high explanatory power of this construct ($R^2_{\text{adj}} = 0.692$) demonstrates that integrating economic, informational, and individual factors provides a robust framework for understanding sustainable technological modernization. In social science research, an R^2 above 0.40 indicates strong explanatory power (Yusuf et al., 2020).

The socioeconomic environment plays a central role. Access to credit (H1: $\beta = 0.245$, $p < 0.01$) positively influences adoption, with a small effect size ($f^2 = 0.083$). Technical assistance (H2: $\beta = 0.151$, $p < 0.01$, $f^2 = 0.027$) also shows a positive association in the main specification, but this path did not survive the alternative-normalization robustness check (Section 4.1) and should be interpreted with caution. This indicates that isolated credit or extension interventions have limited impact without broader institutional support. Technical assistance bridges the gap between innovation and field application, reducing knowledge gaps inherent to sustainable practices (Osumba et al., 2021). Credit enables “trialability,” providing liquidity for producers to test capital-intensive practices before scaling up (Pannell et al., 2006). These institutional mechanisms are reinforced by collective organizations (H3: $\beta = 0.160$, $p < 0.01$), which facilitate information exchange through peer networks (Souza Filho et al., 2011).

Farm characteristics also matter, though with modest effects. Water availability (H6: $\beta = 0.057$, $p < 0.05$) and possession of machinery (H7: $\beta = 0.126$, $p < 0.01$) were confirmed to play a role. Access to technical information sources shows a positive association with adoption in the main specification (H8: $\beta = 0.233$, $p < 0.01$; $f^2 = 0.082$), consistent with informational infrastructure—including internet connectivity and specialized media—being relevant for managing sustainable intensification requirements (Giua et al., 2021); however, as with H2, this specific direct path did not survive the alternative-normalization robustness check (Section 4.1), and we discuss why below.

Farmer characteristics define cognitive capacity. Education level (H9: $\beta = 0.157$, $p < 0.01$; $f^2 = 0.043$) contributes positively but does not constitute an isolated solution (Franchini et al., 2011). Regarding age (H10), the positive coefficient ($\beta = 0.113$) indicates that higher proportions of younger producers (under 45 years) are associated with greater adoption. However, the sharp decline in this demographic—from 38.79% in 2006 to 29.14% in 2017—represents a structural threat to future adoption. This directional finding is a direct consequence of measurement-model refinement rather than an ad hoc reinterpretation. The age construct was initially specified with six observable variables spanning the full age distribution of rural producers (under 25; 25–35; 35–45; 45–55; 55–65; and 65 years or older; Appendix A). During refinement (Section 2.3), the three oldest brackets did not meet the retention criteria and were removed, while the three youngest brackets (AF1–AF3, covering producers under 45) were retained with adequate loadings (0.710–0.867; Table 3). Because the six original brackets partition the same producer population in each micro-region, a higher share of younger producers is arithmetically the mirror image of a lower share of

older producers. The positive coefficient on the retained AF construct is therefore consistent with—not a departure from—the original theoretical expectation that a larger share of older producers is associated with lower technology adoption; the refinement process simply identified the younger end of the age distribution as the statistically stronger empirical proxy for this relationship.

This analysis uses census-based data aggregated to 558 micro-regions. Unlike individual farm surveys with limited geographic scope, this approach reduces sample selection bias relative to small farm surveys and provides complete census coverage, though the resulting inferences are macro-level and ecological—describing relationships among micro-region aggregates rather than individual farm behavior—and remain subject to spatial aggregation effects and modifiable-areal-unit sensitivity.

4.3. The Role of Collective Organizations in Resource Access

Collective organizations (CO) emerge as fundamental catalysts for sustainable agricultural modernization. Hypotheses H4 ($\beta = 0.733, p < 0.01$) and H5 ($\beta = 0.746, p < 0.01$) were confirmed, with large effect sizes ($f^2 = 1.161$ and 1.256 , respectively). Based on Cohen's (1988) criteria, these values indicate a substantial practical effect, exceeding those of individual-level predictors.

Cooperatives mitigate market failures by reducing transaction costs that often exclude smaller agents from formal markets (Neves et al., 2021). The large effect on technical assistance (H5) indicates that cooperatives complement or substitute state-provided extension services, offering more specialized and continuous support (Weybright et al., 2024). Similarly, the influence on credit access (H4) underscores the importance of credit cooperatives and collective bargaining power required by financial institutions (Jiang et al., 2024).

In a sector characterized by productive duality, collective participation is a strategic economic necessity, not merely a social trait. These organizations provide structural support that enables producers to overcome limited individual endowments, sharing and mitigating the technical and financial risks associated with new technologies (Ma et al., 2023). These effect sizes should nonetheless be interpreted with some caution: the HTMT analysis (Section 3.1; Appendix A, Table A2) indicates limited discriminant validity between CO and AC (HTMT = 1.028) and between CO and ATA (HTMT = 1.147), meaning collective organizations, credit access, and technical assistance are not fully statistically distinguishable in this model. The magnitude of H4 and H5 is therefore best read as evidence for a broader cooperative-centered institutional dimension—rather than as three fully independent, precisely separable effects—a distinction that does not overturn the substantive conclusion that cooperatives are central to resource access, but does temper how finely that conclusion can be decomposed with the current measurement model.

4.4. Impacts on the Gross Value of Production (GVP)

Technology adoption positively affects GVP (H11: $\beta = 0.179, p < 0.01$), though with a small effect size ($f^2 = 0.023$). This suggests that while soil conservation and technical inputs are fundamental for productivity, their revenue impact is mediated by external factors such as price volatility and climatic stability (Lee, 2026).

Collective organizations (H12: $\beta = 0.223, p < 0.01$) and technical assistance (H13: $\beta = 0.182, p < 0.01$) also show positive associations with economic outcomes in the main specification. Neither path, however, survived the alternative-normalization robustness check (Section 4.1): CO's direct effect on GVP became non-significant, though CO's effect on AST—the other route through which collective organizations influence economic outcomes—strengthened substantially, so the broader conclusion that cooperative bargaining power matters for GVP is not overturned, only the specific direct CO $\rightarrow$ GVP

and ATA → GVP paths reported here. Access to technical information (H14: $\beta = 0.215$, $p < 0.01$) further enhances GVP by reducing information asymmetry and enabling data-driven decisions (Bolfe et al., 2020).

Together, these determinants explain 47.4% of GVP variance ($R^2_{\text{adj}} = 0.474$), considered robust for economic performance models given agriculture's inherent instability (Yusuf et al., 2020). These results reinforce the central premise: overcoming productive duality requires integrating sustainable practices with institutional support and information infrastructure (Vieira Filho & Fishlow, 2017). These results suggest that integrating sustainable practices with institutional support mechanisms and information infrastructure is closely associated with stronger economic performance from technological modernization, though the cross-sectional design of this study precludes establishing this relationship as strictly causal.

5. Conclusions

This study identified the socioeconomic determinants of sustainable technology adoption and their influence on the Gross Value of Production (GVP) in Brazilian agriculture. The evidence demonstrates that sustainable technological modernization is a systemic process in which institutional support, informational infrastructure, and cognitive capacity outweigh the mere availability of physical resources.

Main findings. Three results are particularly noteworthy. First, collective organizations—especially cooperatives—serve as structural catalysts for both credit access and technical assistance, with effect sizes ($f^2 = 1.161$ and 1.256) that far exceed all other predictors. Second, technical information sources (digital connectivity and specialized media) significantly and robustly influence GVP; their positive association with adoption, though present in the main specification, did not survive the alternative-normalization robustness check (Section 4.1) and is reported with corresponding caution. This underscores the importance of rural informational infrastructure primarily through its economic-outcome channel. Third, the relatively small individual effects of credit and technical assistance indicate that isolated interventions are insufficient without complementary institutional arrangements, and the technical assistance path itself was not robust to normalization choice, reinforcing the case for institutional, rather than isolated, interventions.

Policy implications. Strategies to promote sustainable agriculture must move beyond credit lines. Interventions should focus on three pillars: (i) strengthening cooperativism to manage transaction costs and risks; (ii) investing in rural connectivity to support data-driven decision-making; and (iii) establishing targeted programs for younger farmers, whose propensity for innovation directly affects sectoral resilience.

Limitations and future research. The analysis is constrained by two main factors. First, the model does not capture external variables such as climate variability and global price fluctuations, which affect GVP beyond farm-level decisions.

Second, the study relies on 2017 Census data, as the subsequent census had not been published at the time of this research. While this does not compromise the validity of the structural relationships identified, the results should be interpreted within the institutional and economic context of that period.

Third, because the data are cross-sectional, the structural relationships estimated by PLS-SEM should be interpreted as statistical associations consistent with the hypothesized model rather than as strict causal effects; unobserved micro-region heterogeneity and reverse-causality pathways cannot be ruled out. Reverse causality is particularly plausible for the paths terminating in GVP: more productive micro-regions may be better able to attract or sustain cooperatives, machinery investment, information infrastructure, and

technical assistance, rather than these institutional factors being purely exogenous drivers of GVP.

Fourth, because the unit of analysis is the micro-region rather than the individual farm, the results are subject to ecological-inference limitations and modifiable-area-unit sensitivity: relationships observed among micro-region aggregates do not necessarily hold at the level of individual farms, and different aggregation boundaries could yield different estimates.

Fifth, the HTMT analysis (Section 3.1; Appendix A, Table A2) identified discriminant-validity violations for 13 of the 45 construct pairs, concentrated around ATA and CO—both measured with only two retained indicators—with six pairs exceeding the conservative threshold of 1.00. This limits the precision with which AC, ATA, CO, and, to a lesser extent, PME can be treated as fully independent constructs, and should be considered when interpreting the magnitude and relative ranking of their structural effects. Enriching the ATA and CO measurement blocks, or respecifying them as a single higher-order institutional-support construct, is identified as a priority for future model refinement.

Sixth, the census-based indicators were normalized by number of properties, area, or personnel employed following the established precedent (Section 2.3; Gomes et al., 2024; Xavier et al., 2022). A robustness check re-estimating the model with a single, NP-only normalization (Section 4.1, Table 5) confirms that most structural paths are stable, but four paths—ATA → AST (H2), ATA → GVP (H13), CO → GVP (H12), and STI → AST (H8)—lose statistical significance under this alternative specification, and a fifth (AF → AST, H10) becomes marginal. These are precisely the paths connecting the constructs already flagged for weak discriminant validity in the HTMT analysis (ATA, CO, STI), reinforcing that conclusions about these constructs' individually estimated direct effects should be treated as provisional pending the measurement-model refinements discussed above, even though the broader role of collective organizations in adoption and GVP is, if anything, corroborated by the same check. (A separate robustness check excluding the weakest indicator, AW3, was also completed—see Section 3.1—and left all path coefficients materially unchanged.) Future research using longitudinal data could track how adoption patterns respond to climatic events and policy changes.

Conclusion. Addressing the persistent duality of Brazilian agriculture requires more than distributing credit or promoting individual technologies. Sustainable intensification depends on integrating conservation practices with robust institutional networks and modern information support. Institutional support and information infrastructure thus appear to be key enabling conditions for sustainable technologies to translate into stronger economic outcomes.

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Appendix A

Appendix A.1. Initial Set of Observable Variables (2017 Agricultural Census)

Table A1 lists all 42 observable variables initially selected from the 2017 Agricultural Census (IBGE, 2019) to represent the theoretical constructs (Figure 1), before measurement-model refinement. All counts are establishment-level census totals, normalized by the total number of properties (NP), the total area of properties (AP), or the total personnel employed (PE) in the corresponding micro-region, following the denominator logic described in Section 2.3. Variables retained in the final measurement model are cross-referenced to their code in Table 3; variables not listed in Table 3 were eliminated during the iterative refinement described in Section 2.3 (standardized loading below 0.40, or removal improving the construct's AVE/CR). Four retained indicators (AST3, ATA2, STI2, LE1) are reported in Table 3 with a denominator (AP or PE) that differs from the NP denominator used for the rest of their construct; this was confirmed by the corresponding author to be correct (AST3 and LE1 are normalized by personnel employed (PE), and ATA2 and STI2 by area of properties (AP)) and is reflected accordingly in the Denom. column below.

Table A1. Initial set of 42 observable variables selected from the 2017 Agricultural Census, and their status after measurement-model refinement.

Construct	Code	Original Observable Variable (2017 Agricultural Census)	Denom.	Status in Final Model
AST—Adopting sustainable technologies	AST1	Establishments using fertilizers (organic and/or chemical)	NP	AST1 (retained)
	AST2	Establishments using crop rotation	NP	AST2 (retained)
	AST3	Establishments using soil correctives	PE	AST3 (retained)
	AST4	Establishments using the no-till (straw) system	NP	AST4 (retained)
AC—Access to credit	AC1	Establishments with bank credit (incl. PRONAF, PROCERA and other government programs)	NP	AC1 (retained)
	AC2	Establishments with credit from credit cooperatives	NP	AC2 (retained)
	AC3	Establishments with credit from governments (federal, state, and/or municipal, outside bank-channeled rural credit)	NP	AC3 (retained)
ATA—Access to technical assistance	ATA1	Establishments with government technical assistance	NP	Eliminated
	ATA2	Establishments with own or contracted technical assistance	AP	ATA2 (retained)
	ATA3	Establishments with technical assistance from cooperatives	NP	ATA3 (retained)
	ATA4	Establishments with technical assistance from integrator firms	NP	Eliminated
CO—Collective organizations	CO1	Establishments where the producer belonged to a cooperative	NP	CO1 (retained)
	CO2	Establishments where the producer belonged to a professional/class entity	NP	Eliminated
	CO3	Establishments where the producer belonged to an association or producer movement	NP	Eliminated
	CO4	Establishments where the producer participated in technical meetings and seminars	NP	CO4 (retained)

Table A1. Cont.

Construct	Code	Original Observable Variable (2017 Agricultural Census)	Denom.	Status in Final Model
AW—Availability of water	AW1	Establishments with access to water from springs (protected or not)	NP	AW1 (retained)
	AW2	Establishments with access to water from rivers/streams (protected or not)	NP	AW2 (retained)
	AW3	Establishments with access to water from deep artesian wells	NP	AW3 (retained)
	AW4	Establishments with access to water from cisterns	NP	Eliminated
PME—Productive machinery and equipment	PME1	Establishments owning tractors	NP	PME1 (retained)
	PME2	Establishments owning seeders/planters	NP	PME2 (retained)
	PME3	Establishments owning fertilizer spreaders, harvesters, and/or lime spreaders	NP	PME3 (retained)
STI—Sources of technical information	STI1	Establishments with access to technical information via magazines	NP	STI1 (retained)
	STI2	Establishments with access to technical information via newspapers	AP	STI2 (retained)
	STI3	Establishments with access to technical information via television	NP	Eliminated
	STI4	Establishments with access to technical information via radio	NP	Eliminated
	STI5	Establishments with access to technical information via internet-connected devices	NP	STI5 (retained)
LE—Level of education	LE1	Producer completed higher education	PE	LE1 (retained)
	LE2	Producer completed regular high school (2nd degree)	NP	Eliminated
	LE3	Producer completed former “científico/clásico” track (middle school, 2nd cycle)	NP	Eliminated
	LE4	Producer completed regular elementary school (1st degree)	NP	Eliminated
	LE5	Producer completed former “ginasial” track (middle school, 1st cycle)	NP	LE5 (retained, labeled “Former high school, 1st cycle”)
	LE6	Producer completed former primary school (elementary)	NP	LE6 (retained)
AF—Age of farmers	AF1	Producer aged under 25 years	NP	AF1 (retained)
	AF2	Producer aged 25 to under 35 years	NP	AF2 (retained)
	AF3	Producer aged 35 to under 45 years	NP	AF3 (retained)
	AF4	Producer aged 45 to under 55 years	NP	Eliminated
	AF5	Producer aged 55 to under 65 years	NP	Eliminated
	AF6	Producer aged 65 years or older	NP	Eliminated
GVP—Gross Value of Production	GVP1	Total Gross Value of Production (BRL)	NP	lgvp1 = log(GVP1) (retained)
	GVP2	Total Gross Value of Production (BRL)	AP	GVP2 (retained)
	GVP3	Total Gross Value of Production (BRL)	PE	Eliminated

Source: research results, based on the 2017 Agricultural Census (IBGE, 2019). Note: NP—number of properties; AP—total area of properties; PE—total personnel employed. “Eliminated” indicates the variable did not meet retention criteria in the final measurement model (Section 2.3, Table 3).

Appendix A.2. Heterotrait–Monotrait (HTMT) Ratio Matrix

Table A2 reports the Heterotrait–Monotrait (HTMT) ratio for all 45 construct pairs, computed in SmartPLS as an additional, more conservative discriminant-validity check requested during review (see Section 3.1 for discussion). Values shown in red exceed the conservative $HTMT \leq 0.85$ threshold (Henseler et al., 2015); several of these exceed 1.00.

Table A2. Heterotrait–Monotrait (HTMT) ratio matrix.

	AC	AF	AST	ATA	AW	CO	GVP	LE	PME
AF	0.336								
AST	0.894	0.355							
ATA	1.038	0.553	1.130						
AW	0.479	0.339	0.618	0.556					
CO	1.028	0.472	0.944	1.147	0.601				
GVP	0.661	0.548	0.845	1.069	0.742	0.893			
LE	0.459	0.769	0.734	0.798	0.933	0.689	0.780		
PME	0.774	0.499	0.808	0.904	0.651	0.950	0.973	0.757	
STI	0.472	0.542	0.840	1.180	0.647	0.740	0.819	0.799	0.635

Source: research results (SmartPLS 3 output). Note: values in red exceed the conservative HTMT ≤ 0.85 threshold (Henseler et al., 2015); AC—access to credit; AF—age of farmers (share of younger producers); AST—adopting sustainable technologies; ATA—access to technical assistance; AW—availability of water; CO—collective organizations; GVP—Gross Value of Production; LE—level of education; PME—productive machinery and equipment; STI—sources of technical information.

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