Socioeconomic determinants of sustainable technology adoption and its influence on Brazilian agricultural GVP

Determinantes socioeconômicos da adoção de tecnologias sustentáveis e sua influência no VBP agrícola brasileiro

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Abstract: This study identifies socioeconomic determinants of sustainable technology adoption and their influence on Gross Value of Production (GVP) in Brazil's agricultural sector. Using 2017 Agricultural Census data from 558 micro-regions and Partial Least Squares Structural Equation Modeling (PLS-SEM), the research examines interactions between farm characteristics, technological choices, and economic performance. Findings indicate that adoption is a systemic process driven by institutional, informational, and individual factors (R^2_{adj}= 0.692). Collective organizations act as catalysts for accessing credit and technical assistance, mitigating market failures, while informational infrastructure significantly impacts GVP (R^2_{adj}= 0.474). The study concludes that overcoming productive duality requires a systemic approach integrating sustainable practices with institutional networks. Policy interventions should expand rural cooperativism, digital connectivity, and education for younger farmers. This research provides a validated framework for sustainable intensification and addresses a gap in the literature on the financial performance of sustainable agriculture.
Keywords: Climate change, collective organizations, structural equation modeling, sustainable agriculture.

Resumo: Este estudo identifica os determinantes socioeconômicos da adoção de tecnologias sustentáveis e sua influência no Valor Bruto da Produção (VBP) no setor agrícola do Brasil. Utilizando dados do Censo Agropecuário de 2017 de 558 microrregiões e a Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM), a pesquisa examina as interações entre as características das propriedades, as escolhas tecnológicas e o desempenho econômico. Os resultados indicam que a adoção é um processo sistêmico impulsionado por fatores institucionais, informacionais e individuais (R^2_{aju} = 0,692). As organizações coletivas atuam como catalisadoras do acesso a crédito e à assistência técnica, mitigando falhas de mercado, enquanto a infraestrutura informacional impacta significativamente o VBP (R^2_{aju} = 0,474). O estudo conclui que a superação da dualidade produtiva requer uma abordagem sistêmica que integre práticas sustentáveis às redes institucionais. As intervenções políticas devem ampliar o cooperativismo rural, a conectividade digital e a educação para agricultores mais jovens. Esta pesquisa fornece uma estrutura validada para a intensificação sustentável e preenche uma lacuna na literatura sobre o desempenho financeiro da agricultura sustentável.
Palavras-chave: Mudanças climáticas, organizações coletivas, modelagem de equações estruturais, agricultura sustentável.

1. Introdução

The impact of climate change on food production is associated with rising global temperatures and increased levels of atmospheric carbon dioxide (CO_2)—one of the primary greenhouse gases—which contribute to the occurrence of extreme weather events, such as droughts, heavy rainfall, heatwaves, cold snaps, and shifts in precipitation patterns1. These temperature variations can affect agricultural productivity across various countries, impacting crops such as cotton, rice, barley, sugarcane, sunflower, cassava, maize, soybean, and sorghum (MALHI *et al*., 2021).

Technological intensification in the agricultural sector primarily aims to increase productivity to enhance food production. However, in many cases, such strategies can have adverse effects on the soil. These consequences include declines in soil organic matter and biological diversity, increased erosion and physical degradation, reduced nutrient-use efficiency in cropping systems, groundwater pollution, and increased greenhouse gas (GHG) emissions (KOPITTKE *et al*., 2019, KABATO *et al*., 2025). Soil degradation mainly involves the loss of essential biological, physical, and chemical characteristics necessary for plant development (GAO *et al*., 2024).

Using sustainable technologies on farms is fundamental for enhancing the resilience of production systems to climate variability, increasing productivity, and conserving natural resources such as water, biodiversity, and soil (OGWU and KOSOE, 2025). Technologies contributing to soil conservation include crop rotation, no-till systems, and inputs, correctives, and fertilizers (MANDA *et al.*, 2016; TOPA *et al.*, 2025). In the Brazilian agricultural sector, the adoption of soil conservation technologies by rural producers remains low. In 2017, out of the total 5.07 million rural properties in Brazil, 946.60 thousand used crop rotation (18.66% of the national total), 553.38 thousand used the no-till system (10.91% of the national total), 2.14 million used fertilizers (42.27% of the national total), and 728.54 thousand used soil correctives (14.36% of the national total) (IBGE, 2017).

Adopting technology in the agricultural sector is a complex process shaped by environmental, cultural, economic, institutional, political, and social factors. These factors can be grouped into categories: (a) characteristics of the socio-economic environment in which the farm is located, (b) characteristics of the farm, and (c) characteristics of the farmer (MUNGIA and LLEWELLYN, 2020; PROCÓPIO *et al*., 2024; PROCÓPIO, 2024).

The Brazilian agricultural sector is characterized by a duality in the realities of rural producers' living conditions and economic activity levels. On the one hand, there is a group of technical and specialized agents focused on the production of food and raw materials for processing industries and for domestic and international markets. On the other hand, a portion of Brazilian rural producers live in a state of socioeconomic vulnerability, with production primarily intended for family subsistence. These producers require financial resources, access to land, and specific technologies to increase productivity and output (PEREIRA *et al*., 2024).

In 2017, most rural properties in the country had low agricultural productivity, with approximately 3.73 million rural establishments generating an annual Gross Value of Production (GVP) of up to BRL 25,000 (approximately US$7,837), representing 73.98% of the total (IBGE, 2017). Despite the potential of sustainable technologies to mitigate climate impacts and enhance economic outcomes, the complex interplay among socioeconomic drivers, technology adoption, and their effects on the Gross Value of Production (GVP) remains underexplored in the Brazilian context (PROCÓPIO, 2024; TANURE *et al*., 2024).

Therefore, this study aims to identify the socioeconomic determinants of sustainable technology adoption and analyze their influence on the Gross Value of Production (GVP) in the Brazilian agricultural sector. By employing Structural Equation Modeling (SEM), we examine the complex interactions among farm-level characteristics, technological choices, and economic performance to elucidate the structural barriers that perpetuate the productive duality of Brazilian agriculture.

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 is the official survey of the Brazilian agricultural sector, collecting data on land use, technological patterns in 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

To properly understand the technology adoption process in the agricultural sector, it is necessary to reformulate the traditional adoption model, which treats the decision as binary (adopt or not adopt), to model the phenomenon as a dynamic learning process of the rural producer across several stages. The general aspect to be considered 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 and 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 and experience on the use of technologies in agricultural production systems, thereby contributing to technology adoption (H3) in the field (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 and 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 and GOYARI, 2018). Individuals' age negatively influences the technology adoption process in the rural sector (H10). Older rural producers may exhibit lower energy levels, have a shorter planning horizon (compared to younger individuals), and show greater resistance to changes required 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 the Gross Value of Production (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 the 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 the GVP by professionalizing farm management and applying productive inputs more precisely (H13) (DANSO-ABBEAM *et al.*, 2018). Finally, access to diverse sources of technical information also positively influences the 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.

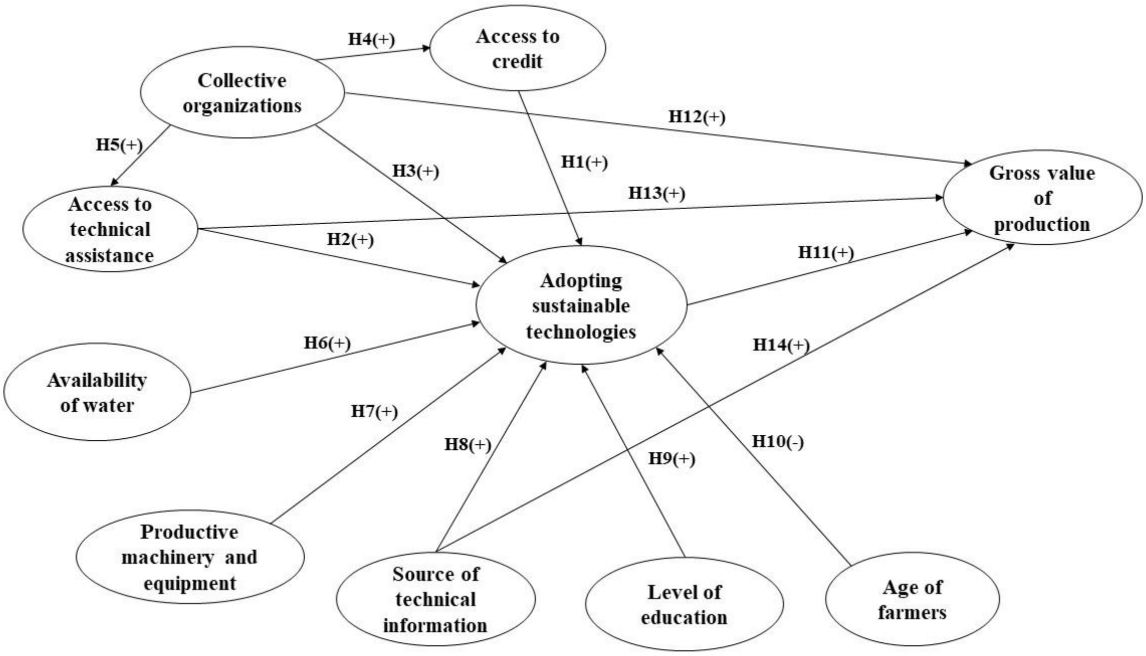
Table 1. Hypotheses of the theoretical model

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 existence 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).

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 and 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 and 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). All statistical procedures were performed using SmartPLS® 3 software

3. Results and Discussion

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 threshold 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 exceed 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 (AVE > 0.50; CR > 0.70) (Table 2). This was achieved by removing low-loading observable variables and applying a logarithmic transformation to the variable composing the GVP. The logarithmic transformation is essential for reducing skewness in the data distribution and improving the model's predictive properties (FÁVERO *et al*., 2014).

Table 2. Correlation matrix between latent variables

	AC	**ATA**	**AT**	**AW**	**FI**	**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 – Source of technical information; AF – Age of farmers; PME – Productive machinery and equipment; LE – Level of education; CO – Collective organizations; GVP – Gross Value of Production.

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).

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) (other types of resources provided outside rural credit lines)/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 – Gushing deep water wells/np	0.379
PME – Productive machinery and equipment	PME1 – Tractors/np	0.889
	PME2 – Seeder/planter/np	0.928
	PME3 – Fertilizer spreader, harvesters, or lime spreader/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 (secondary 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.

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 and SILVA, 2019).

3.2 Structural model

The structural model was evaluated using Pearson's coefficients of determination, multicollinearity analysis, f^2 effect sizes, and coefficient significance (RINGLE *et al*., 2014; BIDO and SILVA, 2019) (Table 4). The 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 value achieved was 47.40% (0.474) (Table 4).

Collinearity was assessed using variance inflation factors (VIFs) for the latent variables. In the PLS-SEM approach, the VIF value must be within the 0.20-5.00 range 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 between constructs	Hypotheses	VIF	f^2	Structural coefficient (β)	Standard error	Significance (*p-value*)	R^2	Adjusted R^2
AC -> AST	H1	2.371	0.083	0.245	0.038	0.000***	0.696	0.692
ATA -> AST	H2	2.756	0.027	0.151	0.050	0.003***		
AW -> AST	H6	1.502	0.007	0.057	0.029	0.049**		
STI -> AST	H8	2.185	0.082	0.233	0.039	0.000***		
AF -> AST	H10	1.396	0.030	0.113	0.026	0.000***		
PME-> AST	H7	3.123	0.017	0.126	0.047	0.008***		

LE -> AST	H9	1.890	0.043	0.157	0.037	0.000***		
CO -> AST	H3	4.667	0.018	0.160	0.056	0.004***		
ATA -> GVP	H13	2.723	0.023	0.182	0.066	0.006***		
AST -> GVP	H11	2.697	0.023	0.179	0.053	0.001***	0.478	0.474
STI -> GVP	H14	1.870	0.047	0.215	0.049	0.000***		
CO -> GVP	H12	2.903	0.033	0.223	0.060	0.000***		
CO -> AC	H4	1.000	1.161	0.733	0.027	0.000***	0.537	0.536
CO -> ATA	H5	1.000	1.256	0.746	0.026	0.000***	0.557	0.556

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 – Source 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 of structural coefficients were obtained using the bootstrapping resampling technique with 5,000 repetitions.

3.3 Determinants of Sustainable Technology Adoption

The structural model results indicate that the adoption of sustainable technologies (AST) in the Brazilian agricultural sector is a complex, multidimensional phenomenon, shaped by socioeconomic factors and the characteristics of both properties and rural producers. The high explanatory power of this construct (R^2_{adj}= 0.692) indicates that integrating economic, informational, and individual factors provides a robust framework for understanding sustainable technological modernization in the Brazilian agricultural sector. In social science research, an R^2 value greater than 0.40 typically indicates strong explanatory power (YUSUF *et al*., 2020). In this sense, the validation of hypotheses H1, H2, H6, H7, H8, H9, and H10 reinforces the premise that sustainable intensification is driven by a complex interplay between a producer’s resource endowment—such as credit and the possession of machinery and equipment—and their cognitive capacity, shaped by education and access to information. Therefore, overcoming the sector's duality requires addressing these multiple dimensions simultaneously, as they collectively shape the producer's capacity to navigate the risks and requirements of the transition to sustainable farming.

This process is primarily shaped by the socioeconomic environment, in which access to credit (H1: β = 0.245, $p < 0.01$) and technical assistance (H2: β = 0.151, $p < 0.01$) positively influence the adoption of sustainable technologies. However, based on Cohen’s (1988) criteria, both variables showed small effect sizes (f^2 = 0.083 and f^2 = 0.027, respectively), indicating that, although statistically significant, their individual ability to drive adoption is limited when they are not part of a broader support framework. The confirmation of H2 indicates that technical assistance helps bridge the gap between innovation and field application. Because sustainable practices often involve a learning curve, guidance is necessary to reduce knowledge gaps and improve farm management (OSUMBA *et al*., 2021). Similarly, credit (H1) is required for "*trialability*," as it provides the liquidity needed for producers to test capital-intensive practices, such as no-till systems and crop rotation, before adopting them at scale (PANNELL *et al*., 2006). This institutional support is reinforced by participation in collective organizations (H3: $\beta = 0.160$, $p < 0.01$; $f^2 = 0.018$), which facilitates information flow through peer-to-peer networks (SOUZA FILHO *et al*., 2011).

Regarding farm characteristics, H6 ($\beta = 0.057$, $p < 0.05$; $f^2 = 0.007$) was supported, validating the theoretical relationship between water availability and the technology adoption process. Similarly, H7 (presence of machinery and equipment) ($\beta = 0.126$, $p < 0.01$; $f^2 = 0.017$) was confirmed with a small effect size. The theoretical validation of the relationship between access to technical information sources and technology adoption was also confirmed (H8: $\beta = 0.233$, $p < 0.01$), with a small effect size ($f^2 = 0.082$). This suggests that informational infrastructure—including internet connectivity and specialized media—is vital for producers to manage the specific requirements of sustainable intensification (GIUA *et al*., 2021).

Finally, the characteristics of the farmer define the cognitive capacity to manage these resources. Education level (H9: $\beta = 0.157$, $p < 0.01$) contributes with a small effect ($f^2 = 0.043$), corroborating the conclusion that schooling provides the skills necessary to handle complex biological recommendations (FRANCHINI *et al.*, 2011), but does not constitute an isolated solution. Regarding age (H10), the positive effect ($\beta = 0.113$, $p < 0.01$; $f^2 = 0.030$) indicates that younger individuals (under 45 years old) are more proactive. While this group shows a small but significant effect on adoption due to greater openness to innovation, the sharp decline in the number of producers under 45 (from 38.79% in 2006 to 29.14% in 2017) represents a structural threat.

3.4 The Role of Collective Organizations in Resource Access

The structural model highlights collective organizations (CO) 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 $f^2 = 1.256$, respectively). Based on Cohen's (1988) criteria, these values indicate a dominant practical impact within the system, far exceeding the individual effects of other predictors.

These results suggest that cooperatives and associations serve as essential institutional mechanisms for mitigating market failures in the Brazilian agricultural sector. By organizing individual producers, these entities reduce the high transaction costs that often exclude smaller or vulnerable agents from formal markets (NEVES *et al*., 2021). The large effect observed for technical assistance (H5) indicates that cooperatives often complement, or even substitute, the State's role in rural extension by providing more specialized and continuous technical support (WEYBRIGHT *et al.*, 2024). Similarly, the influence on credit access (H4) underscores the importance of credit cooperatives and the collective bargaining power needed to meet financial institutions' demands (JIANG *et al*., 2024).

In a sector characterized by productive duality, participation in collective organizations is a strategic economic necessity rather than a mere social trait. These organizations provide the structural support producers need to overcome limited individual resource endowments. Ultimately, this institutional strength enables the 'trialability' discussed in previous sections, as the technical and financial risks associated with new technologies are shared and mitigated through the collective framework (MA *et al*., 2023).

4.3 Impacts on the Gross Value of Production (GVP)

The results confirm that the adoption of sustainable technologies (H11: $\beta = 0.179$, $p < 0.01$) positively affects the Gross Value of Production (GVP), albeit with a small effect size ($f^2 = 0.023$). This suggests that while soil conservation and technical inputs are fundamental for maintaining productivity, their impact on total revenue is mediated by external factors, such as market price volatility and climatic stability (LEE, 2026).

The model further indicates that participation in collective organizations (H12: $\beta = 0.223$, $p < 0.01$; f2 = 0.033) and access to technical assistance (H13: $\beta = 0.182$, $p < 0.01$; $f^2 = 0.023$) positively affect the economic outcomes of rural producers. These findings suggest that professionalized farm management and the increased bargaining power provided by cooperatives are as decisive for GVP growth as the technology itself (Ma et al., 2023). Access to technical information sources (H14: $\beta = 0.215$, $p < 0.01$; $f^2 = 0.047$) also positively influences GVP. In modern Brazilian agriculture, the ability to process market data and technical recommendations appears to be a determining factor in optimizing financial returns and reducing information asymmetry (BOLFE *et al*., 2020).

Overall, the cumulative effect of these determinants explains 47.4% of the variance in GVP (R^2_{adj} = 0.474). This explanatory power is considered robust for economic performance models, particularly given the agricultural sector's inherent instability (YUSUF *et al*., 2020). These results reinforce the central premise of this study: overcoming the productive duality in

Brazilian agriculture requires a systemic approach (VIEIRA FILHO and FISHLOW, 2017). Sustainable practices must be combined with institutional support and high-quality informational infrastructure to ensure that sustainable technological modernization translates into superior economic performance.

5. Final considerations

This study identified the socioeconomic determinants of sustainable technology adoption and their influence on the Gross Value of Production (GVP) in the Brazilian agricultural sector. The results indicate that sustainable technological modernization is a systemic process in which institutional support, informational infrastructure, and cognitive capacity are more influential than the availability of physical resources. A fundamental finding is the role of collective organizations in the sustainable intensification of the Brazilian agricultural sector, serving as key catalysts for credit and technical assistance, as indicated by observed effect sizes that show that cooperatives and associations are structural components in addressing productive duality. Furthermore, the relative impact of technical information sources on both adoption and GVP suggests that digital connectivity and specialized media are important components for promoting conservation agriculture.

From a public policy perspective, these results suggest that strategies to promote sustainable agriculture must go beyond credit lines. Interventions should focus on three pillars: strengthening cooperativism to manage transaction costs and risks; investing in rural connectivity to support decision-making; and establishing programs to support younger farmers, whose propensity for innovation affects the sector's resilience.

Finally, although the model accounts for part of the variance in GVP, its scope is constrained by variables such as climate and global prices. Future research using longitudinal data could track how adoption patterns change in response to climatic events. In summary, addressing the duality of Brazilian agriculture requires integrating sustainable practices with institutional networks and information support to sustain both economic and environmental performance.

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