Advancements in Agricultural Development
Volume 6, Issue 3, 2025
agdevresearch.org

Factors Influencing Tennessee Farmers' Adoption of Technology: A Survey of Tennessee Agricultural Enhancement Program Participants

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Abstract

Farmers adopt new technologies to be competitive and farm efficiently. This study explored what factors influence technology adoption among row crop and livestock farmers in Tennessee. Utilizing Rogers' Diffusion of Innovations Theory, this study investigated the impact of economic benefits, cost, peer influence, compatibility, and demographic characteristics on the adoption decisions of farmers. This study employed a mixed-methods approach by combining the Delphi technique and survey research. Thirty experts participated in the Delphi and 675 farmers completed the quantitative instrument. The results of the Delphi study provided a list of technologies that farmers are currently looking to adopt along with what promotes and hinders adoption. Survey research revealed that economic benefits are the most influential factor in adoption, while cost and compatibility can serve as barriers. Demographic characteristics such as education level, farm size, farm income, and years of experience significantly influence adoption decisions. Binary logistic regression and Bayesian regression analyses indicated that adopter categories, innovativeness, economic factors, demographics, and socioeconomic factors significantly influence adoption decisions. The conceptual model developed from this study suggests the inclusion of various influential factors to improve the predictability of adoption decisions.

Article History

Received: July 10, 2025
Accepted: August 10, 2025
Published: September 29, 2025

Keywords

adoption; technology; farmers; SDG 9: Industry, Innovation, & Infrastructure

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Introduction and Problem Statement

The adoption of innovations and technologies by farmers enhances agricultural enterprises in multiple ways, from reduced inputs to increased production, profits, and sustainability. This research supports the United Nation's goal to help farmers foster innovation to be more sustainable. Loevinsohn, et al. (2013, p. 2), described agricultural technology as "the means and methods of producing crops and livestock." The goal of technology itself is the production of a good or service that is easier, less expensive, or less laborious while simultaneously increasing efficiency. Technologies are designed to save time and reduce effort by making the applicant's work easier than it would have been without the innovation (Bonabana-Wabbi, 2002). The factors that influence the decision to adopt or not adopt a technology are all influenced by an individual's characteristics, access to information regarding the technology, peer influence, and a myriad of other factors (Rogers, 2003). Previous research on the transformation of agriculture has mostly concentrated on the technical aspects of integrating new technologies to enhance agricultural practices and output. A growing number of studies conducted in recent years have looked at how farmers are utilizing new technologies and the key factors that influence their decision to adopt technologies (Carlisle, 2016; Li et al., 2019; Yaseen et al., 2023).. According to Mwangi and Kariuki (2015, p. 209), "researchers should clearly state how they are defining technology adoption so that they can develop an appropriate tool to measure it." Despite substantial work on technology adoption in agriculture, few statewide studies integrate farmer elicited technology priorities with multivariate adoption modeling that compares row-crop and beef farmers within the same study. This study addresses that gap by combining a three-round Delphi with a state-wide quantitative survey to describe how economic benefits, cost, compatibility, peer influence, and producer characteristics influence adoption decision in Tennessee.

Theoretical and Conceptual Framework

The theoretical framework for this study includes Rogers' (2003; Rogers et al., 2014) Diffusion of Innovations Theory and Ajzen's (1991) Theory of Planned Behavior (TPB). The Theory of Rational Choice (TRC) was also used in this study to further explain the motivational behaviors of farmers when looking to adopt a new technology (Smith, 2012). The principal components of the Diffusion of Innovations Theory incorporated in this study encompasses the definition of innovation, the social networks through which information is disseminated, influential factors in deciding to adopt an innovation, and the categories of adopters as defined by Rogers (2003). These foundational components of the theory are equally significant to the postulation of each respective theory. The framework for adopting innovations is best described as a theory of dissemination of information and individual behavior or as a theory of communication and collective behavior (Edison & Geissler, 2003; Nyairo et al., 2021). Hence, the incorporation of TPB into this study.

According to Wright (2004), it can take prolonged periods for individuals to incorporate new technologies and concepts into routine practices and procedures. Once individuals are introduced to an innovation, people begin their decision-making process, which includes discovery and understanding, evaluation of benefits and costs, selecting a choice, execution, and confirmation (Rogers, 2003). These internal processes are parts of cognitive behavior and have influences that go beyond the individual level. By communicating ideas with others through dissemination, the community, as a whole, engages in discovering the advantages and disadvantages of an innovation. While an individual's decisions can be hard to observe, the adoption rate of an entire group within a social network such as the agricultural industry is more easily observed (Takahashi et al., 2020).

The TRC assumes that individuals make informed decisions by performing a cost-benefit analysis of each alternative and choosing the option that maximizes their utility (Ajzen, 1991). In agricultural production, this theory suggests that a farmer will adopt an innovation if they think that it will provide more benefits than costs, otherwise known as a return on investment. An additional theory that is relevant to the adoption of new technology is the TPB. The TPB suggests that an individual's behaviors are primarily influenced by three factors: behavior, subjective norms, and perceived behavioral control (Doran et al., 2020). In agriculture, a farmer's decision to adopt a new technology could potentially be influenced by their perceptions of how effective the technology is, the opinions of their fellow farmers, and how difficult it is to use. The TRC highlights the importance of knowing what behaviors farmers believe to be important and their expectations of how likely they can exude these behaviors (Pannell et al., 2006).

The conceptual framework for the study was based on the work of Meijer et al. (2015, p. 1) who developed a conceptual model that captures "the characteristics of the farmer, the external environment, and the characteristics of agricultural innovations as the extrinsic factors that influence adoption." There are numerous factors, both direct and indirect, that impact a farmer's adoption decision, including individual characteristics, environmental factors, features of the innovation, and an aggregation of the influence from both peers and other third parties. All these factors interact with one another to affect a farmer's final decision. Combined, these "intrinsic and extrinsic factors interact and drive adoption and influence a farmers' decision-making process" (Meijer et al., 2015, p. 40). This work demonstrated how the four attributes of economic benefits, cost of technology, compatibility, and peer influence collectively affected a producer's adoption decision.

Purpose

The primary purpose of this study was to identify the factors that had the greatest impact on Tennessee farmers' decisions to adopt new technology. The research objectives included the following:

1. Identify the key technologies that expert row crop and livestock producers prioritize for adoption on their farms.
2. Describe the readiness and willingness of farmers to adopt new technologies based on adopter category and level of innovativeness.

3. Describe the influential factors impacting technology adoption.
4. Explain farmers' decisions to adopt or not adopt technology based on adopter category, innovativeness, and influential factors.
5. Develop a comprehensive model to illustrate the decision-making process regarding the adoption of specific technologies in row crops and beef cattle production.

Methods

This study asked experts what technologies were most important and farmers whether they would adopt or not adopt identified agricultural production practices. This study employed a mixed-methods approach to understand the factors influencing Tennessee farmers' adoption of new technologies. A Delphi study (Dalkey & Helmer, 1963) and survey research employing descriptives, inferential statistics, and binary logistic regression were used to address the research objectives. The Delphi study was conducted with 28 expert farmers and 2 extension specialists, identified by the Tennessee Department of Agriculture, to determine the key technologies farmers are considering adopting. The study progressed through three rounds to reach a consensus, focusing on influential factors such as economic benefits, compatibility, cost, and peer influence. The first round involved open-ended questions, followed by ranking these factors in subsequent rounds. By the third round, a consensus was achieved for technologies that were important to the farmer participants (See Table 1) along with what factors ultimately had the greatest influence on adoption decisions.

Table 1

Technologies Reported from Delphi Study

Technologies Livestock Farmers are Looking to Adopt	Technologies Row Crop Farmers are Looking to Adopt
Artificial Insemination	Biologicals
Embryonic Transfer	Cover Crops
Forage Innovations	Data Management Software
GIS Technologies	Fertility Technology
Invitro Fertilization	GIS Technologies
Medications/Vaccinations	Pesticides
Sexed Semen	Precision Agricultural Technologies (PATs)
Smartphone Apps	Seed Genetic Traits
	Smartphone Apps
	Tillage Innovations

Using Dillman's (2000) system of five compatible contacts, the quantitative survey was distributed to 5,420 Tennessee farmers participating in the Tennessee Agricultural Enhancement Program, a successful cost-share program in the state. There were 675 responses for a return rate of 12.4%. Incomplete responses were removed from the database used for the regression analyses, which left (*n* = 675; 576 livestock farmers and 99 row crop farmers) actual subjects in the study. Generally accepted protocols and procedures to mitigate nonresponse error were followed, and late respondents (the later 50%) were compared to early respondents as prescribed by Lindner et al. (2001) and Lindner (2002). Using an independent samples t-test, it was determined there was no significant difference for each independent variable between early (*n* = 427) and late (*n* = 241) respondents. The independent variables included adopter categories, innovativeness, economic benefits, cost, compatibility, peer influence, education, years of farming experience, operation size, and annual farm income. The dependent variables were the adoption decisions for specific technologies, which varied between row crop and livestock farmers.

Survey participants were asked to self-categorize themselves in adopter categories (1 = Innovators, 2 = Early Adopters, 3 = Early Majority, 4 = Late Majority, 5 = Laggards). To avoid response bias, descriptions of each category were provided, not the name of each category. In addition, a 5-item innovativeness scale was completed by farmers. Innovativeness scores were interpreted as follows: *Strongly Agree* = 5.00 – 5.99, *Agree* = 6 – 6.49, *Neutral* = 6.50 – 7.49, *Disagree* = 7.50 – 8.49, *Strongly Disagree* = 8.50 – 10.00. The perceived importance of Economic benefits, Cost of technology, Compatibility, and Peer influence to adopting new technology used Likert-type items interpreted as: Very important = 5.00 – 4.51, Important = 4.50 – 3.51, Neutral = 3.50 – 2.51, Unimportant = 2.50 – 1.51, Very unimportant = 1.50 – 1.00. Binary responses (Adopt or Not Adopt) were collected to determine which specific technologies farmers would adopt.

Descriptive statistics and binary logistic regression predicted the likelihood of technology adoption based on independent variables. Descriptive statistics, such as means and standard deviations, were reported for adopter categories, innovativeness, economic benefits, compatibility, cost, peer influence, education, years of farming experience, size of operation, and annual farm income. All tests used a significance threshold of $\alpha = 0.05$ set a priori. The odds ratio (Exp(β)) was calculated to identify the magnitude of the relationship of adoption to the other independent variables in the study. A multicollinearity test was conducted using the Variance Inflation Factor to determine the level of collinearity between independent variables. A backward stepwise binary logistic regression procedure was used to predict adoption and each of the influential factors and demographics, for the purpose of better understanding what causes a farmer to adopt a technology. Finally, a Hosmer and Lemeshow Test was conducted to assess the goodness of fit of the regression logistic models (Hosmer et al., 2013). Bayesian regression was also employed for variables where binary logistic regression was inconclusive, as Bayesian regression is well suited to handle model data with small sample sizes and can provide accurate estimations (McNeish, 2016).

Findings

The Delphi study was utilized to generate a list of technologies that farmers were looking to adopt. The statewide survey revealed that livestock farmers emphasized medications, reproductive technologies, and forage innovations, while row crop farmers prioritized seed genetic traits, cover crops, and precision agriculture technologies (PATs). Economic benefits were the primary driver of adoption decisions, followed by compatibility, cost, and peer influence, with insufficient economic returns as the main barrier. The participants were asked to rank technologies by importance, with lower mean scores indicating higher priority based on participant rankings (1 = most important, 10 = least important). The livestock farmers indicated that reproductive technologies, forage innovations, and medications were the technologies they were prioritizing to adopt for their operations. The row crop producers reported that seed genetic traits, cover crops, and precision agricultural technologies were the technologies that they were considering for adoption. The findings suggest that livestock farmers prioritize technologies enhancing animal health and reproduction, while row crop farmers focus on yield-enhancing and precision technologies, driven primarily by economic returns.

Adoption Readiness by Adopter Category and Innovativeness

Livestock farmers (n = 576) predominantly identified in the Early Majority (38.4%) and Late Majority (35.9%), with lower innovativeness scores (M = 8.79–9.16). Row crop farmers (n = 99) leaned toward being classified as the Early Majority (44.4%) and Early Adopters (23.2%), with higher levels of innovativeness (M = 7.00–8.96). ANOVA revealed significant innovativeness differences across adopter categories ($p < 0.05$). For livestock farmers, Early Adopters were more innovative than Late Majority ($p < 0.01$) and Laggards ($p < 0.01$). For row crop farmers, Innovators surpassed Early Majority ($p < 0.02$), Late Majority ($p < 0.01$), and Laggards ($p < 0.04$). Cohen's d confirmed that level of innovativeness had a medium effect on technology adoption (Cohen's d = 0.71 for livestock, 0.73 for row crop; $p < 0.001$). These results indicate row crop farmers are more innovative and more readily adopt new technologies, aligning with their larger, more commercial operations, while livestock farmers are more cautious, reflecting smaller farms.

Influential Factors on Technology Adoption

Livestock farmers commonly held bachelor's degrees (39%), with the Early Majority having the highest education levels. Their operations averaged 50–100 head of cattle, with Laggards managing smaller herds (25–50 head). Experience increased from Innovators (10–15 years) to Laggards (20+ years), with income levels typically being below $50,000. Row crop farmers reported higher incomes (28% earned > $1,000,000) and larger operations (56% with 1,000–5,000 acres), with 74% farming 20+ years.

Influential factors included economic benefits, cost, compatibility, and peer influence. Participants were asked how influential each of these factors were on their decision to adopt new technologies. Economic benefits (M = 3.99; SD = 0.42 for row crop, M = 3.41; SD = 0.49 for livestock) and cost (M = 3.81, SD = 0.60; M = 3.47, SD = 0.52) were the most influential factors, followed by compatibility (M = 3.74, SD = 0.38; M = 3.09, SD = 0.34) and peer influence (M = 3.39; SD = 0.53; M = 3.09, SD = 0.33). Those with higher education, larger operations, and higher incomes were more likely to adopt new technologies. Farmers with 10–15 years' experience showed the highest adoption rates, suggesting a balance of experience and openness to innovation.

Predicting Adoption Decisions

Table 2 summarizes significant predictors ($p < 0.05$) and their odds ratios (OR), indicating the likelihood of adoption per unit increase in the predictor.

Table 2

Significant Predictors of Technology Adoption

Technology	Group	Predictor	OR	*p-value*	Nagelkerke R^2
Artificial Insemination	Livestock	Operation Size (25–50 head)	2.65	0.03	0.15
		Operation Size (200+ head)	4.05	0.01	
		Adopter Cat. (EM vs. Laggards)	6.01	<0.001	
Embryonic Transfer	Livestock	Education (MS vs. HS Diploma)	2.65	0.01	0.15
		Operation Size (200+ head)	5.39	0.01	
		Adopter Cat. (EM vs. Laggards)	3.27	0.02	
Forages	Livestock	Adopter Cat. (EM vs. Laggards)	3.32	0.05	0.09
		Years Farming (5–10 vs. 1–5 years)	8.62	0.05	
GIS Technologies	Livestock	Compatibility	2.17	0.01	0.02
Medications	Livestock	Years Farming (20+ vs. <5 years)	5.21	0.03	0.10
Sexed Semen	Livestock	Operation Size (100–200 head)	3.45	0.01	0.11
		Adopter Cat. (EM vs. Laggards)	4.40	0.01	
Smartphone Apps	Livestock	Annual Income (>$250,000 vs. <$50,000)	7.81	0.05	0.13
		Adopter Cat. (EA vs. Laggards)	3.58	0.02	
Biologicals	Row Crop	Innovativeness	20.04	0.03	0.75
		Education (MS vs. HS Diploma)	9.86	0.03	
		Adopter Cat. (Innovators vs. Laggards)	23.45	0.00	
		Peer Influence	0.41	0.01	
Cover Crops	Row Crop	Cost	0.17	0.05	0.00
Data Management	Row Crop	Adopter Cat. (EA vs. Laggards)	27.48	0.03	0.52
GIS Technologies	Row Crop	Operation Size (1,000–5,000 acres)	16.50	0.04	0.12

Note. Odds Ratio (OR) > 1 indicates increased adoption likelihood; OR < 1 indicates decreased likelihood. Nagelkerke R^2 reflects model explanatory power; 0.4 or higher suggest a strong relationship.

For livestock technologies, larger operations are more likely to adopt artificial insemination (OR = 2.65-4.05), embryonic transfer (OR = 5.39), and sexed semen (OR = 3.45, reflecting economies of scale. Early Majority farmers were more likely to adopt artificial insemination (OR = 6.01), embryonic transfer (OR = 3.27), forage innovations (OR = 3.32), and sexed semen (OR = 4.40) compared to Laggards, indicating faster adoption among moderately innovative farmers. Years of farming experience (20+ years, OR = 5.21) predicted medication use, likely due to established practices. Compatibility (OR = 2.17) was key for GIS technologies, emphasizing integration with existing systems.

For row crop technologies, Innovativeness (OR = 20.04) and master's-level education (OR = 9.86) strongly predicted biologicals adoption, with Innovators (OR = 23.45) leading, though peer influence reduced adoption (OR = 0.41), suggesting skepticism among peers. Higher costs decreased cover crop adoption (OR = 0.17), highlighting economic barriers. Early Adopters (OR = 27.48) drove data management adoption, reflecting their tech-savvy nature. Larger operations (OR = 16.50) readily adopted GIS technology, aligning with precision farming needs. For technologies with multicollinearity (fertility, pesticides, PATs, seed genetic traits, smartphone apps, tillage innovations), principal components (PC1: cost/economics; PC2: compatibility/operation size/income) were used. PC2 significantly predicted pesticide (OR = 4.16) and smartphone app (OR = 3.85) adoption, indicating combined influence of farm scale and compatibility. Models showed strong explanatory power (Nagelkerke R Square = 0.08–0.75) and good fit (Hosmer-Lemeshow $p > 0.05$, except GIS Livestock, $p = 0.00$). Seed genetic traits results were inconclusive due to low variability.

Comprehensive Adoption Model

The conceptual model (see Figure 1) integrates significant findings and expands current understandings. Economic benefits consistently increased adoption, while cost and compatibility often reduced it. Adopter categories, peer influence, operation size, income, education, years of experience, and innovativeness had mixed effects, varying by technology. Newer technologies (e.g., biologicals) were favored by Innovators/Early Adopters, while older technologies (e.g., forage innovations) were adopted by Late Majority/Laggards. Principal components (PC1, PC2) confirmed the combined influence of economic factors, compatibility, and operation size.

Economic benefits were the only factor that did not negatively influence the adoption of certain technologies. Compatibility had mixed effects across technologies, indicating that integration with existing systems can either facilitate or hinder adoption depending on the context. Cost had a varying impact on technology adoption. This finding is likely caused by differing levels of income amounts for row crop and livestock farmer subjects. This supports Kinyangi (2014) who suggested the influence of cost on technology adoption is dependent on whether the farmers possess the required resources to purchase the technology. For newer technologies, adopter categories positively influenced adoption. However, when analyzing older technologies, adopter categories had a negative influence on adoption. The model underscores that economic benefits and farm scale drive adoption, with adopter categories shaping technology-specific patterns. Economic benefits and larger operations consistently drove adoption, with adopter categories influencing technology-specific outcomes. These findings provide insights for targeting extension efforts to enhance technology uptake among Tennessee farmers.

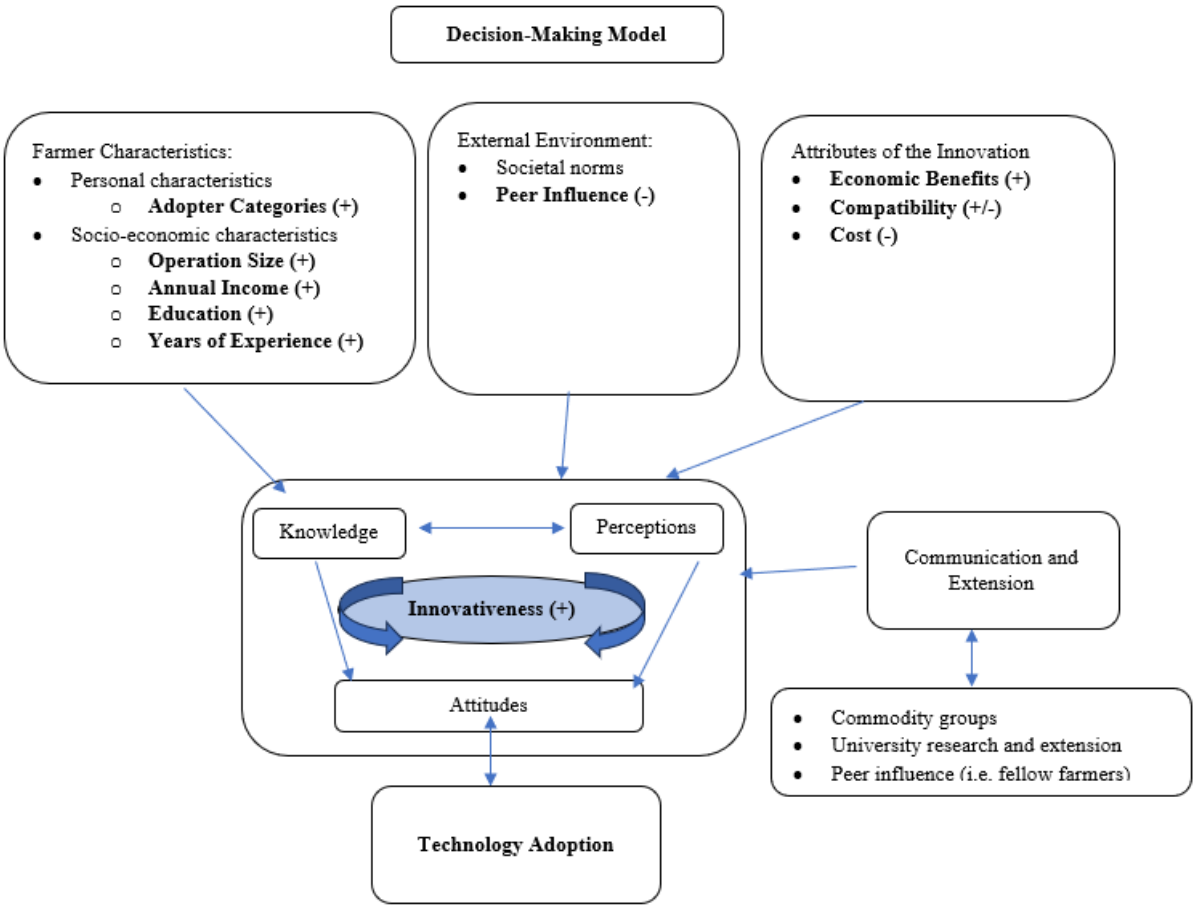
Conclusions, Discussion, and Recommendations

Using a Delphi study and survey research, we examined how farmers prioritize certain technologies and what factors, such as economic benefits, costs, compatibility, and peer influence, impacted their decisions. We found that the adoption of innovative technologies is essential for improving sustainability, reducing production costs, and increasing overall productivity. We affirmed numerous aspects of Rogers' (2003) Diffusion of Innovations Theory. Consistent with Rogers' adopter classifications, our findings indicated that Innovators and Early

Adopters were significantly more likely to adopt new technologies than the Late Majority and Laggards. The impact of peer influence alights with the Theory of Planned Behavior's subjective norms, including perception of what fellow farmers value can either accelerate or hinder adoption. The mixed effects of compatibility are consistent with the perceived behavioral control since certain technologies are perceived to be easier to integrate and thus more readily adopted. The Theory of Rational Choice (Smith, 2012) opines that people make decisions by performing a cost-benefit analysis of various options and choosing the one that results in the highest levels of utility. This study's findings relate to this theory by showing how farmers adopt technologies that provide more utility for themselves and their operations. Economic benefits were ranked as the most influential factor in adoption decisions for both livestock and row crop farmers. Costs, however, posed significant barriers for certain technologies, deterring adoption. Other factors, including compatibility with existing practices and peer influence, also played crucial roles in determining whether technologies would be embraced. Demographic characteristics, such as education level, years of farming experience, and operation size, were found to significantly influence technology adoption. Farmers with higher levels of education and larger operations were more likely to adopt new technologies, as were those with more years of farming experience. Farmers with 10 to 15 years of experience exhibited the highest adoption rates, likely reflecting a balance of practical experience and openness to new ideas. Larger operations also demonstrated a greater willingness to adopt advanced technologies. Figure 1 synthesizes our empirical results with Diffusion of Innovations, the Theory of Planned Behavior, and rational choice mechanisms, highlighting how perceived economic benefits and farm size interact with norms and compatibility constraints to shape adoption.

Figure 1

Influential Factors to Technology Adoption Model



Note. Adapted from Meijer et al. (2015) and modified with findings from the study.

The bolded items in the model were found to be statistically significant to technology adoption. The plus symbols (+) signify variables that positively influenced adoption while the minus symbols (-) indicate variables that negatively influenced adoption. This study revealed the critical roles that economics, cost, compatibility, and peer influence have on technology adoption decisions. Through the Delphi study, technologies were identified that farmers are actively looking to adopt. Innovativeness was influential to technology adoption, but an improved measurement of innovativeness was recommended for future research. This innovativeness metric could include questions that asked about openness to new ideas, risk tolerance levels, management styles, and adoption experiences, and assess the farmers' attitude toward continued learning. The study contributed to agricultural development by providing insight into the relationships between adopter categories, innovativeness, economics, compatibility, peer influence, and certain demographics influence a farmer's decision to ultimately adopt or not adopt specific agricultural technologies. This work should be replicated in other states or regions to aid researchers in predicting technology adoption among farmers. The model needed to include the use of multivariate dependent variables to capture more variance and improve its robustness, such as measuring different stages of adoption (no adoption, experimental use, partial adoption, and full adoption) to enhance accuracy and reliability. Given the importance of economic benefits as seen in this study and others (Bellon & Reeves, 2002; Karlan et al., 2014; Rogers, 2003), economic benefits need to be emphasized to promote the adoption of new technologies and in educational programs to increase adoption rates among farmers. We discovered compatibility negatively influences certain technologies, so educators should focus on addressing knowledge gaps to align existing and new technologies. Smaller operations were less open to adopting technologies, indicating a need for educational programs addressing scalability issues. Finally, initiatives to create a culture of innovation for farmers, tailored to different adopter categories and varying innovativeness levels, are recommended.

Acknowledgments

Funding Information: This work is supported by the United States Department of Agriculture National Institute of Food and Agriculture, NEXTGEN Program, Award #2023-7044-40157.

Conflict of interest: There are no conflicts of interest.

Previous Dissemination: This article is a truncated version of a dissertation at Tennessee State University. The dissertation was not yet published at the time of this article submission.

Artificial Intelligence: AI was not used for this study.

Author Contribution Statement: **D. Morris** – formal analysis, investigation, and writing original draft; **J. Ricketts** – formal analysis, writing, reviewing, and editing; **D. Hochreiter** – writing, reviewing, and editing.

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