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The analysis of producers' technology investment intentions within the framework of extended theory of planned behavior

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ABSTRACT

This study is based on the Theory of Planned Behavior and expands this main framework by including the constructs of education, knowledge acquisition and access to financial resources. In this study conducted on 270 farmers in Konya -an important agricultural region of Turkey-, a stratified sampling design was employed with a survey instrument adapted from previously validated measurements. Robust reliability and validity were confirmed for constructs related to attitude, subjective norms, perceived behavioral control, knowledge acquisition and access to financial resources through Partial Least Squares Structural Equation Modeling approach. The results obtained show that attitude, subjective norms and knowledge acquisition significantly increase the perceived behavioral control of farmers. On the other hand, there is an indirect relationship between perceived behavioral control and technology investment intention through the access to finance, which indicates that access to financial resources emerges as a pivotal factor determining technological investment intentions. These results imply that it is important to improve the farmers' financial capacity and information support to promote technology adoption. In this context, policy makers and agencies working in the field of agricultural development need to spearhead the process of the financial barriers and knowledge resources, by first selecting credit facilities, providing government subsidies and later knowledge transfer.

1. Introduction

New technologies enhance societal welfare across numerous sectors by improving efficiency, reducing the necessity for human labor, and enabling large-scale production. Agriculture is one such sector, where the increasing utilization of technology has facilitated the provision of sustenance for billions of people worldwide as agricultural enterprises have a significant impact on meeting national and global food needs and economic development, particularly in rural areas (Pawlak & Kołodziejczak, 2020). As such, the adoption and integration of advanced technologies in agriculture has become a relevant necessity in order to enhance productivity and resource efficiency, and also to facilitate the sustainable agricultural practices (Malorgio & Marangon, 2021). Emerging technologies like precision agriculture, Internet of Things (IoT) devices, and artificial intelligence can bring transformative advancements in conventional agricultural practices and provide practical solutions to problems faced today (Usigbe et al., 2024; GAO, 2024). On the other hand, it must be noted that the decision-making processes leading to technology investments in agricultural enterprises are complex, and they would not be complete without a comprehensive examination and research.

Technological innovations can help farmers realize increases in productivity in the agricultural field. The new solutions correspond to eliminating problems, such as rising temperatures due to climate change, soil erosion and flood, and also rising and decreasing commodity prices (Rose & Chilvers, 2018). The new approaches that rely on remote sensing, data-operated crop management systems, and advanced water practices enable agricultural entities to economize their resources, reduce waste and get better protection against variability in weather. Furthermore, digital and mobile applications enable small farmers to

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trade products in markets, provide the farmers with current weather information as well as helping them access financial services. This achievement raises their rank in global value chains (Mgendi, 2024). These developments reveal that technology is not just a tool, but an important factor in achieving radical changes in agriculture.

The acceptance of new techniques in agriculture is formed by the interaction of economic, social, and ecological factors (Abadi Ghadim & Pannell, 1999; Ruzzante et al., 2021). This process is not limited to financial dimensions, it can also be motivated by people's behaviors, cultural norms along with the advantages gained from innovations in technology (Aubert et al., 2012; Tey & Brindal, 2012). Generally, farmers evaluate the impacts of technology on their total gain, labor productivity as well as risk, along with the cost of the new tech options (Lowenberg-DeBoer & Erickson, 2019; Ruzzante et al., 2021). In addition to economic and technical factors, trust in technology providers, perceived ease of use, and compatibility with existing applications are other factors that contribute significantly to the adoption processes (Aubert et al., 2012; Yeo & Keske, 2024). For example, while precision agriculture applications seem feasible in terms of the yield improvement and the environment protection, the adoption of smarts with these technologies varies by the regions as a result of the various reasons like accessibility of technology, complexity perception and farmers' education levels (Barnes et al., 2019; Vecchio et al., 2020; John et al., 2023). Similarly, this diverseness of factors influencing the technology diffusion tells us that it is also important for us to do detailed research on the determinants of the technology adoption in different regional and socio-economic contexts (Ruzzante et al., 2021; Tey & Brindal, 2012).

The implementation of technology in agriculture also improves farmers' working conditions and augments their income and satisfaction. In the study conducted by Liu et al. (2024), it was established that the adoption of technology resulted in an increase in happiness and life satisfaction of farmers. However, the adoption of new technologies can sometimes be a gradual and challenging process for farmers, and their decision-making regarding investments in new technologies requires theoretical assessment. Usually, small-scale farmers consider the latest technological tools to be costly, complex, and difficult to implement (Kendall et al., 2022). Data shows that despite traditional modes of cultivation spelling the sustainable agriculture technology, the doubts of the long-term returns of investments and certain other risks are the barriers to technologies adoption. Also, doubts about long-term returns on investment, as well as certain other risks, act as barriers to the adoption of technology. Also, the absence of technical support and training opportunities to use technology deepens these adverse perceptions and makes technology harder to use (Fadeyi et al., 2022; Mizik, 2023; Smidt & Jokonya, 2021). Moreover, social elements, peer pressure, and social norms are the major keys to redefine the attitude of farmers towards technology. For instance, studies have established that the likelihood of farmers trialing or adopting an innovation is greater when approved by an agricultural advisor or when their peers follow suit (Tran- Nam & Tiet, 2022; Xu et al., 2022; Beaman et al., 2021).

Also, understanding farmers' approach to technology investments are essential. Often, farmers experience challenges, such as lack of access to credit, lack of infrastructure, or a split of the land they own that make decision-making quite difficult (Ogada et al., 2014; Lemecha, 2023; Cafer & Rikoon, 2018;). To overcome these challenges and to increase the rates of technology adoption, specific measures like subsidies for financing, vocational courses, and improving infrastructure are important (ISF Advisors, 2014 and IISD, 2015). In addition, to ensure the efficient role of technological progress and its continuity in farmers' lives, the technology should be in line with satisfying their needs and high expectation levels in addition to being sustainable (Rizzo et al., 2024; Rosário et al., 2022). In recent years, the importance of psychological factors in the adoption of new technologies in agriculture have become increasingly prominent. In this field, farmers' intentions and behaviors regarding innovations have been examined using various theoretical approaches, especially the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). For example, according to previous studies cognitive biases, such as risk perception and uncertainty avoidance can create inconsistencies between adoption intention and actual behavior (Bi & Zou, 2024); perceived usefulness and ease of use significantly affect intention (Mahattanakhun & Suvittawat, 2023); in terms of the role of self-norms, farmers' past experiences and expectations shape their current attitudes (Schukat & Heise, 2021); and the level of education increases the tendency to adopt low-carbon agricultural technologies (Zhao & Hong, 2021).

Using structural equation modeling (SEM), Jiang et al. (2022) reported that positive attitudes and perception of efficiency directly affect intentions towards low-carbon technologies; Kaliky et al. (2023) found that self-confidence and resource accessibility are the main factors determining perceived behavioral control. Yap et al. (2023) also emphasized that gender, age, and education level directly shape behavioral intentions by affecting the perception of technology readiness. All these studies show that farmers' cognitive, emotional, and social dimensions play a critical role in the adoption processes of technological innovations, thus strengthening the rationale for preferring TPB in this study in simultaneously evaluating social norms and actual control components.

The Theory of Planned Behavior (TPB) (Ajzen, 1991) provides a framework to address the deficiencies in this area by emphasizing the importance of attitudes, subjective norms, and perceived behavioral control in determining technology adoption decisions. The use of this theory in the agricultural sector allows for a better and deeper description of the factors that boost or prevent modernization of agriculture. However, the results of the study conducted by Waiswa et al. (2024) showed that, there were significant differences across the countries studied in terms of the impact of the TPB constructs on intentions to adopt new technology. While several studies have examined technology adoption behavior of farmers through this framework, there is a lack of research on this issue in Türkiye. In order to address this gap in the literature, this study focuses on the technology adoption of farmers in Konya, which is one of the agriculture centers in Türkiye. The term technology adoption is confined to three inter-related categories of digital agriculture solutions already commercially available in Konya: (i) precision-agriculture hardware such as GPS-guided variable-rate applicators and yield-monitoring sensors; (ii) smart agriculture technologies, and (iii) innovative irrigation systems. Konya was selected as the study area not only because of its agricultural scale, but also due to its unique position within Türkiye's agri-technological landscape. As one of country's top-performing agricultural regions in terms of land use, production volume, and mechanization, Konya has become a leading recipient of both public and private investments in agricultural innovation. The region is home to numerous government-backed pilot projects, subsidy schemes, and research partnerships targeting smart farming adoption. These characteristics make Konya a particularly relevant empirical setting for analyzing behavioral factors that influence technology investment decisions under favorable yet unevenly utilized innovation ecosystems.

This research is designed to contribute to or supplement the already existent literature through analysis of the decisions of agricultural businesses on technology investment by incorporating education, knowledge and access to financial resources to the Theory of Planned Behavior (TPB). Additionally, it aims to provide practical insights for policy makers, agricultural stakeholders and technology developers to guide the less inclusive and sustainable adoption of agricultural technologies. This study contributes to the existing literature by extending the Theory of Planned Behavior through the integration of context-specific constructs, such as Information and Knowledge Acquisition (IKA) and Access to Financial Resources (AFR). While previous studies have focused on the direct effects of core TPB variables, our model emphasizes the indirect relationships that better reflect the socio-economic realities of small- and medium-scale farmers in Türkiye. In particular, the study sheds light on the critical role of perceived behavioral control as a pathway between information channels, attitudes, norms and actual investment intentions, offering new insights into the behavioral mechanisms that underlie technology uptake in developing agricultural contexts.

1.1. Theoretical framework and literature review

Ajzen (1991)'s study on the Theory of Planned Behavior (TPB) has been one of the most known and heavily utilized psychological frameworks that are aimed at both understanding and predicting human behavior. According to the TPB framework, human behavior is influenced by three types of factors. These are behavioral beliefs, which are contemplating the likely outcome of the behavior, normative beliefs which consider the expectations of others, and control beliefs which refers to the factors that may facilitate or impede the behavior's performance. (Ajzen, 2011; Bošnjak et al., 2020).

Attitudes refer to the individual's positive or negative evaluation of performing a particular behavior, such as adopting new technology. Social pressures define the example of subjective norms, where an individual is required to either engage or not engage in a particular behavior, most of which is dependent on peers or family's expectations and practices within the community (Godin & Kok, 1996:87). In turn, perceived behavioral control demonstrates an individual's understanding of self-capability of executing a specific behavior, which is determined by resources, knowledge among other constraints (Ajzen, 1991).

The TPB model is useful for analyzing technology acceptance in agricultural businesses because decisions are sometimes made based on personal, social, and contextual characteristics. To illustrate, a farmer's attitude towards investing in precision agriculture could stem from their assessment of its advantages compared to the financial and technical risk it might pose. Also, subjective norms can be influential since a farmer may consider the views of his peers, local agricultural expert, and community figures. Finally, perceived behavioral control is equally important because farmers must make an assessment of whether they have sufficient resources, capabilities, and all necessary effort to adopt and use the agricultural technology (Carli et al., 2017; Tey & Brindal, 2012). By incorporating these aspects, the TPB gives a descriptive view on the behavior analysis of technology adoption. This model reinforces the need to tackle not just the physical and economic difficulties of adoption, but also the social and psychological aspects of the decision (Yang et al., 2024). Investment in specific agricultural technologies is assisted by knowing how such policies can be designed within the motivation and situational context of farmers, which will result in greater sustainable technology adoption.

According to Dissanayake et al. (2022), positive attitude towards technology has direct influence on subjective norm, perception of behavioral control and adoption of new agricultural technology. Similarly, Waiswa et al. (2024) found that positive attitudes (of the smallholder farmers in East Africa), subjective norms and beliefs in success impact the adoption intention of push-pull technology. As stated by Karbo et al. (2024), TPB consistently explains the behavioral intentions of farmers in poor and developing countries but only if social approval and perceived difficulty, or ease, are properly measured. Similarly, Ren and Zhong (2022) showed that Chinese farmers' adoption of straw-returning technology is driven by behavioral attitude, subjective norm and perceived control in aggregate, while Xiang and Guo (2023) reported that attitudes, subjective norms and perceived usefulness significantly promote green control techniques. And also, Li et al. (2020)'s study found that farmers' willingness to use formula fertilizer and soil testing technology is primarily determined by attitudes, subjective norms, and perceived control. Chen et al. (2024) suggested that social and personal norms can activate the intentions of farmers to utilize green prevention and control methods. These findings reinforce TPB's fundamental insight: people will form the intention to adopt (and will eventually adopt) when they have a positive impression of an innovation, perceived social support for its implementation in their context, and high levels of confidence in their ability to implement it.

Adnan et al. (2017) and Akudugu et al. (2023) shed light on socio-economic and situational conditions. Adnan et al. (2017) highlighted social approval and institutional supports for Malaysia's rice farmers, while Akudugu et al. (2023) focused on digital technology adoption during crises where demographics and pandemic-related concerns significantly altered farmers' readiness for adoption. Taken together, all these studies confirmed the basic premise of TPB.

In addition to these, there are also studies in the literature that reach different conclusions. Lou et al. (2021) concluded that subjective norms and perceived behavioral control positively affect tea farmers' intentions to adopt green control technology; however, attitude does not have a significant effect on the intention to adopt the technology. We can interpret this result as social support, and perceptions of control are more important than personal evaluations. Unlike other studies, Valizadeh et al. (2023) emphasized the importance of the mediating role of moral norms and, in this direction, stated in their study that farmers' ethical beliefs increase social influence. Similarly, Zhang et al. (2024) reported that inequality aversion tested together with TPB constructs shows only weak explanatory power in predicting farmers' behavior, and therefore other psychological or contextual factors may overshadow distribution concerns. Broader contextual elements also emerge in the study conducted by Chi and Chien (2022), who argued that environmental and quality concerns, government subsidies, and community networks significantly shape intentions to adopt environmentally sound agricultural systems. Outside the typical TPB framework, Abay et al. (2017) emphasized locus of control as an important psychological determinant, suggesting that farmers who believe their own efforts shape outcomes are more proactive in adopting agricultural innovations. Similarly, Xu et al. (2024) showed that farmland scale (both at the farmer and plot level) interacts with adoption decisions in green production technologies, in part through commercialization rates and machinery investments. Furthermore, Yang et al. (2022) observed that while behavioral intention generally mediates the path from attitude, subjective norm, and perceived behavioral control to final behavior, a positive attitude can sometimes produce direct effects on actual adoption, thus slightly circumventing the usual sequence of the TPB. In this study, Information and Knowledge Acquisition (IKA) was conceptualized as a background factor that may influence farmers' beliefs and behavioral intentions, rather than being directly integrated into the core Theory of Planned Behavior (TPB) constructs like subjective norm. This conceptual choice is grounded in Ajzen's (2011) clarification that exposure to information through various channels—including media, social networks, and institutional sources—functions as a background variable shaping behavioral, normative, and control beliefs, rather than serving as a direct component of the normative structure itself. The concepts of interest and knowledge acquisition (IKA) and subjective norms (SN) may appear to be conceptually similar, as both can include elements of social influence. However, these two structures have fundamentally different functions within the framework of the Theory of Planned Behavior (Ajzen, 1991). Subjective norms express the social pressure felt by important reference persons or groups (e.g., family, friends, colleagues) regarding whether an individual should or should not perform a certain behavior and reflect the individual's normative beliefs about 'what others expect from me.' In this study, IKA is considered as a broader background factor that refers to exposure to information obtained from various sources, such as the media, agricultural extension services, educational activities, and institutional communication. The function of IKA is not to create social expectations or obligations on the individual, but rather to reflect the cognitive and knowledge-based environment that contributes to the formation of farmers' behavioral, normative, and control beliefs (Ajzen, 2011). In this regard, the survey questions used in the study were developed to measure the impact of information obtained from different information channels on farmers. The questions focus on understanding the extent to which these sources are considered effective and reliable, rather than creating normative pressure on farmers.

Other studies have pointed out the value of TPB in understanding the attitudes of farmers towards certain technologies like precision farming tools and decision support systems (Cheng, 2019; Mohr & Kühl, 2021; Wu et al., 2024; Dong et al., 2022). This is supported by Jin et al. (2022), who found in their study of Tanzanian maize farmers that perceived behavioral control is the most important determinant of intention to adopt, and by Dong et al. (2022), who suggested that build on TPB by internally integrating it with the Technology Acceptance Model (TAM) and demonstrating that perceived usefulness and perceived ease of use positively reinforce the constructs already established by TPB. In this study, the 'Access to Financial Resources' (APR) variable was included in the model as both an external control determinant that feeds perceived behavioral control (PBC) and as a result of PBC, going beyond the original structure of the Theory of Planned Behavior (TPB) (see Fig. 1). In the agricultural context, farmers' perception of 'I can make this investment' (PBC) is directly related to their access to financing opportunities; at the same time, farmers with high PBC levels increase their chances of finding financial resources by participating more aggressively in loan applications and investment processes. For this reason, a double-sided arrow in the form of PK ↔ PBC was used in our model. On the other hand, empirical SEM analysis and field literature have emphasized that attitude (A) and subjective norm (SN) have a weak direct effect on technology investment intention (BI), but these two structures shape intention indirectly by strengthening PBC. Therefore, A and SN variables are positioned not directly but as 'A/SN → PBC → BI' on the path to BI. As a result, based on local agricultural reality and empirical findings, a dynamic conceptual framework is developed, in which PBC directly affects both financial resource access and investment intention, while FK reinforces PBC.

1.2. Hypotheses

H1. Producers' attitudes towards technological investments influence their perceived behavioral control.

H2. Producers' attitudes towards technological investments influence their technological investment intention.

H3. Producers' subjective norms influence their perceived behavioral control.

H4. Producers' information and access to knowledge influence their perceived behavioral control.

H5. Producers' education levels influence their knowledge and access to information regarding technological investments.

H6. Producers' education levels influence their attitudes towards technological investments.

H7. Producers' access to financial resources for technological investments influences their technological investment intention.

H8. Producers' perceived behavioral control influences their access to financial resources for technological investments.

2. Methodology

2.1. Study area and data collection

The objective of this exploratory study is to identify the factors that influence the intention of agricultural enterprises to adopt new technologies. Konya was selected as the study area due to its status as a center for agricultural technology firms' marketing activities, the region's agricultural significance, and the prevalence of larger planting areas particularly suitable for technology adoption (see Fig. 2).

The required sample size (n) was calculated to be 270 farmers, according to the following formula, with the population of farmers in Konya being approximately 106,833 (N).

$$n = \frac{\mathrm{N\,P}(1-\mathrm{P})}{(N-1)\sigma^2 + P(1-P)}$$

Where s is the required sample size, N is the population size, P is the population proportion and assumed to be 0.5 for maximum sample size, and σ^2 is the variance. The sample size was determined using a 5 % margin of error and 90 % confidence limits. To this end, a stratified sampling method was implemented, with each district of Konya designated as a separate stratum. The sample size for each stratum was then calculated using proportional allocation based on the number of farmers in that district. The survey was conducted on 270 farms from a total population of 106,833 farmers in the region. The survey instrument was

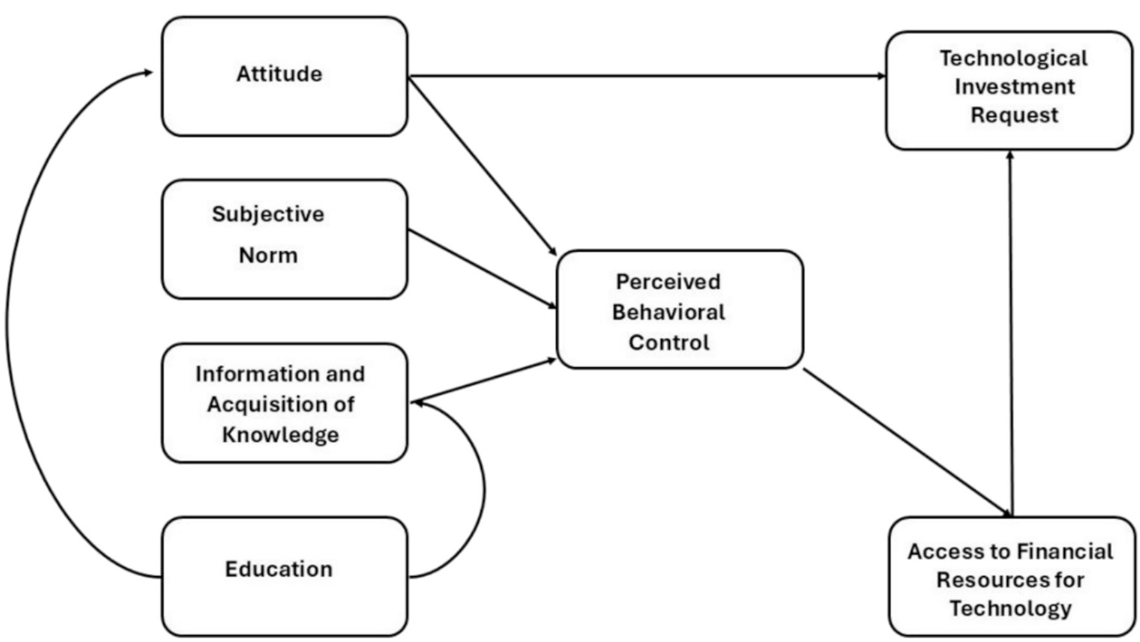

Fig. 1. Extended theory of planned behavior.

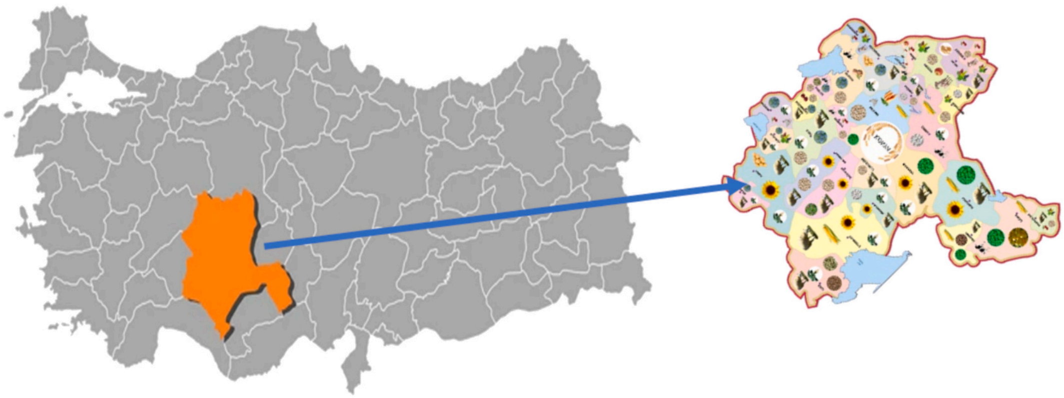

Fig. 2. Study area.

administered through personal interviews, thus ensuring the uniformity and reliability of the results across strata.

In order to design a questionnaire instrument, the measures previously employed (primarily Passarelli et al. (2023)) were adapted, with minor modifications, to align with the specific context of the present research. The questionnaire comprises two sections: one for socioeconomic and operational characteristics of the farms, and a second for the measures of TPB constructs. The measurement of the TPB variables was conducted using a five-point Likert scale, except for the adoption behavior variable, which was measured as a dichotomous scale. The set of descriptors comprised the following: ‘strongly disagree’, ‘disagree’, ‘neither agree nor disagree’, ‘agree’, and ‘strongly agree’.

3. Results

Since the study sets out to quantify technology-investment intention, we rely on partial least squares structural equation modeling (PLS-SEM). PLS-SEM is expressly recommended for small-to-medium samples roughly 50–200 observations because its variance-based estimation retains satisfactory statistical power under such conditions (Hair et al., 2017). Moreover, its component-based logic lets researchers extend the Theory of Planned Behavior (TPB) with context-specific antecedents. Here we can mention information availability and access to finance without over-identification problems. Recent TPB extensions that added constructs such as relational support, moral obligation, or environmental concern have been successfully estimated with PLS-SEM (Canova et al., 2020; Sabina del Castillo et al., 2021). Finally, extensive Monte-Carlo evidence shows that PLS-SEM is robust to pronounced departures from multivariate normality, yielding unbiased path coefficients and reliable standard errors under marked skewness and kurtosis (Hair & Alamer, 2022).

A comprehensive evaluation of the validity and reliability of the study's criteria was conducted to explain technology investment intention within the Theory of Planned Behavior framework. The analysis results indicated that all constructs demonstrated acceptable levels of reliability and validity (see Table 1). The attitude construct, which is measured by four items, exhibits high reliability and validity, with a Cronbach's alpha coefficient of 0.858, a composite reliability (CR) value of 0.904. The Subjective Norm construct also showed valid and reliable measurement, with a Cronbach's alpha value of 0.720, CR value of 0.842. Strong internal consistency is observed in the Information and Knowledge Acquisition construct (measured by five items) with a Cronbach's alpha coefficient of 0.866, and CR value of 0.903. The Perceived Behavioral Control indicators load ranged between 0.869 and 0.911, well above the $\geq$0.708 cut-off that denotes adequate item reliability and convergent validity for reflective measures (Hair et al., 2019; Pereira et al., 2024). The Access to Financial Resources for Technology scale records a Cronbach's α of 0.681 and a composite reliability (CR) of

Table 1
Validity and reliability analysis results.

Indicator	Loading	Cronbach Alpha	AVE	CR
Attitude		0.858	0.703	0.904
ATT1: I think using new technologies is a good thing.	0.786			
ATT2: Using new technologies means greater environmental sustainability.	0.901			
ATT3: Using new technologies means increased value added.	0.864			
ATT4: Using new technologies means increased efficiency.	0.797			
Subjective Norm		0.720	0.640	0.842
SN3: Farmers using new technologies achieve higher yields.	0.781			
SN4: Agricultural experts encourage the use of new technologies in agriculture.	0.805			
SN5: My close friends support me in using new technologies.	0.815			
Information and Knowledge Acquisition		0.866	0.651	0.903
IKA1: I adopt technology when informed by other farmers.	0.780			
IKA2: I adopt technology when I receive information from experts.	0.835			
IKA3: I adopt technology when I observe experts in action.	0.863			
IKA4: I adopt technology when I receive external support.	0.787			
IKA5: I adopt technology when I partner with universities and research centers.	0.766			
Education		1.000	1.000	1.000
EDU: Primary, Secondary, High School, College (2 years), University (4 years)	1.000			
Perceived Behavioral Control				
PBC1: I believe using new technologies is a realistic action for me.	0.911			
PBC2: I think it is possible for me to use new technologies.	0.869			
Technological Investment Intention		1.000	1.000	1.000
TII: Yes, No	1.000			
Access to Financial Resources for Technology		0.681	0.756	0.861
AFR1: When I want to use new technology, I can benefit from government incentives or subsidies.	0.902			
AFR2: When I want to use new technology, I can benefit from bank loans.	0.836			

0.861; α values in the 0.60–0.70 band are acceptable for newly developed or exploratory instruments, while CR values above 0.70 confirm internal consistency (Hair et al., 2019; Taber, 2018). Taken together, since all outer loadings exceed 0.70 and every CR coefficient surpasses 0.70 the measurement model fulfils the convergent-validity criteria proposed by Fornell and Larcker (1981), underscoring its adequacy for the study's theoretical framework. These findings support the study's theoretical framework and validated the adequacy of the measures used to explain technology investment intention in agricultural enterprises. It is important to note that the variables 'Education' and 'Technological Investment Intention' were not treated as reflective latent constructs in the structural model. These variables were collected through the demographic section of the questionnaire as factual, directly observable indicators. Specifically, education level was measured using a single categorical item (ranging from primary school to university), while technological investment intention was measured using a binary response (Yes/No) to indicate whether the respondent planned to invest in new agricultural technologies. As such, these are not multi-item constructs reflecting latent psychological traits but rather single-item factual measures.

The Fornell–Larcker criterion is the established test for discriminant validity in variance-based SEM (see Table 2), requiring that the square root of each construct's average variance extracted (AVE) exceeds its correlations with every other latent construct (Fornell & Larcker, 1981).

The extended TPB model's goodness of fit was assessed utilizing the coefficient of determination (R^2), cross validation redundancy (Q^2) and Standardized Root Mean Square Residual (SRMR) indicators (see Table 3). R^2 values express the explained variance ratios of the dependent variables and indicate the explanatory power of the model. The R^2 value for the Perceived Behavioral Control (PBC) construct was calculated as 0.513, indicating that the explanatory power of the model for this variable is substantial. Although the R^2 values for other constructs are lower, they are calculated at acceptable levels as 0.043 for Attitude (ATT), 0.024 for Information and Knowledge Acquisition (IKA), 0.074 for Technological Investment Intention (TII), and 0.068 for Access to Finance for Technology (AFT). The Q^2 values indicate the predictive power of the model. While the Q^2 value for PBC demonstrates a strong predictive power of 0.394, the Q^2 values for the other constructs range between 0.014 and 0.059, indicating low to moderate predictive power. The SRMR (Standardized Root-Mean-Square Residual) obtained for our structural model is 0.074. This satisfies the widely accepted cut-off of <0.08 originally proposed by Hu and Bentler (1999) for judging overall model fit in covariance- and variance-based SEM. Subsequent PLS-SEM handbooks retain this benchmark, noting that SRMR values below 0.08 (or, in very complex models, below 0.10) indicate that the reproduced correlation matrix does not deviate materially from the observed one (Hair et al., 2021).

The significant positive path from Attitude (ATT) to Perceived Behavioral Control (PBC) ($\beta = 0.447$, $t = 6.884$, $p < 0.001$) supports H1, indicating that positive attitudes towards technological investments indeed strengthen producers' perceived control over adopting technology (see Table 4). The negative relationship between Attitude (ATT) and Technological Investment Intention (TII) ($\beta = -0.121$, $t = 2.088$, $p = 0.037$) suggests a contrary result for H2. Although attitude impacts behavioral control positively, the negative effect on investment intention might indicate a saturation effect. The positive path from Subjective Norms (SN) to Perceived Behavioral Control (PBC) ($\beta = 0.263$, $t = 4.261$, $p < 0.001$) supports H3, showing that subjective norms (social influences) significantly contribute to increasing perceived behavioral control over technological adoption. The positive effect of Information and Knowledge Acquisition (IKA) on Perceived Behavioral Control (PBC) ($\beta = 0.161$, $t = 2.447$, $p = 0.015$) supports H4, suggesting that access to information and knowledge enhances perceived control over technology adoption. Although Education (EDU) significantly impacts both Attitude (ATT) ($\beta = 0.207$, $t = 4.845$, $p < 0.001$) and Information and Knowledge Acquisition (IKA) ($\beta = 0.156$, $t = 2.696$, $p = 0.007$), no direct path to Technological Investment Intention (TII) is examined in the results. This supports the idea that education influences knowledge and attitudes but does not directly determine investment intention. The positive influence of Education (EDU) on Attitude (ATT) ($\beta = 0.207$, $t = 4.845$, $p < 0.001$) supports this hypothesis, confirming that higher educational levels foster positive attitudes towards technological investments. The significant path from Access to Financial Resources (AFR) to Technological Investment Intention (TII) ($\beta = 0.269$, $t = 4.376$, $p < 0.001$) supports H7, showing that the availability of financial resources positively influences the intention to invest in technology. The positive relationship from Perceived Behavioral Control (PBC) to Access to Financial Resources for Technology (AFR) ($\beta = 0.262$, $t = 4.151$, $p < 0.001$) confirming H8, indicates that stronger perceived control over technology adoption enhances access to financial resources for investment.

Table 2
Discriminant validity test of the (Fornell-larcker criteria).

	ATT	IKA	EDU	AFR	PBC	SN	TII
ATT	0.838						
IKA	0.498	0.807					
EDU	0.207	0.156	1.000				
AFR	0.209	0.329	0.073	0.869			
PBC	0.645	0.512	0.182	0.262	0.890		
SN	0.448	0.486	0.063	0.246	0.541	0.800	
TII	−0.065	0.005	0.003	0.244	0.037	0.014	1.000

Table 3
Structural model tests.

Indicator	R2	Q2
ATT	0,043	0,029
IKA	0,024	0,014
PBC	0,513	0,394
TII	0,074	0,059
AFT	0,068	0,040
SRMR	0,074	

4. Discussion and conclusion

The findings of this study support the proposed hypotheses, particularly in demonstrating the positive influence of subjective norms, information access, education, and financial resources on perceived behavioral control and new technology adoption intentions. In this way, it also confirms the results of previous studies (Li et al., 2020; Yang et al., 2022; Dong et al., 2022; Waiswa et al., 2024) suggesting the usefulness and applicability of TPB on explaining the technology adoption in agriculture. As indicated by the findings of the present study, attitude and subjective norm, two of the key constructs of TPB, have been demonstrated to exert a significant positive yet indirect influence on technology adoption through perceived behavioral control. Concurrently, perceived behavioral control has a significant positive indirect effect on technology adoption through access to financial resources. In line with previous literature (Hunecke et al., 2017); Sutherland et al., 2013), our findings suggest that farmers' perceived behavioral control (PBC) regarding technology use is positively associated with their access to financial resources for investment. This relationship can be explained by the fact that perceived behavioral control does not only reflect confidence in using new technologies but also a broader sense of self-efficacy in managing the complex decisions surrounding investment, including financial planning and credit management. Farmers who feel more capable of adopting agricultural technologies are likely to also perceive themselves as more competent in identifying appropriate credit sources, understanding loan conditions, and managing repayment obligations. As highlighted by Dey and Singh (2023), the greater the perceived capability to utilize institutional credit effectively, the

Table 4
Path coefficients for the extended TPB model.

Hypothesis	Path	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values	VIF
H1	ATT ➔ PBC	0.447	0.445	0.065	6.884	0.000	1.435
H2	ATT➔ TII	−0.121	−0.121	0.058	2.088	0.037	1.046
H3	SN➔PBC	0.263	0.263	0.062	4.261	0.000	1.413
H4	IKA➔PBC	0.161	0.165	0.066	2.447	0.015	1.502
H5	EDU➔IKA	0.156	0.155	0.058	2.696	0.007	1.000
H6	EDU➔ATT	0.207	0.207	0.043	4.845	0.000	1.000
H7	AFR➔ TII	0.269	0.272	0.062	4.376	0.000	1.046
H8	PBC➔AFR	0.262	0.260	0.063	4.151	0.000	1.000

stronger the intention to adopt it. Therefore, increased PBC may indirectly enhance access to financial resources by reinforcing farmers' confidence in their ability to manage the financial requirements of technology investment. Within the context of Turkiye, it has been observed that despite the presence of favorable attitudes among farmers towards technological adoption, and their perception of technological competence, their intention to adopt new technology is contingent upon access to financial resources. This finding is in line with Chi and Chien (2022) who reported the significance of government subsidies on technology adoption.

In this study, we found a negative direct effect of attitudes on technology investment intention. While the Theory of Planned Behavior typically posits a positive link between favorable attitudes and behavioral intention, prior empirical studies have also observed inverse or insignificant effects, particularly in contexts where the target behavior has already been widely adopted. In our case, this may indicate that farmers with more favorable attitudes towards technology have already adopted relevant technologies and, therefore, perceive less urgency or necessity for additional investment. This interpretation is supported by Yang et al. (2022), who observed that in mature adoption contexts, perceived behavioral control may exert a stronger influence on intention than attitude. Thus, the negative coefficient in our model may reflect a saturation effect, whereby those most positively inclined towards technology are not the ones planning new investments—because they have already acted.

This study further expands analysis by incorporating Information Acquisition and Access to Financial Resources to the TPB model in order to address main barriers in the adoption of technology. These two constructs have also been incorporated into the TPB model by Passarelli et al. (2023) to investigate technology adoption but they are found insignificant. This can be due to the fact that Passarelli et al. 2023 opted to employ logistic analysis and we have decided to adopt an alternative methodology that will facilitate the analysis of the complex relationships among the latent variables. Furthermore, empirical support for this interpretation is provided by Witzling et al. (2015), who found that information exposure is associated with multiple TPB variables, including perceived behavioral control and behavioral beliefs, in addition to subjective norm. The variability in the strength and direction of these associations highlights the broader cognitive and contextual role of information exposure. In line with this perspective, we treated IKA as an antecedent influencing the formation of TPB variables, thereby enriching the explanatory capacity of the model in understanding farmers' behavioral intentions towards technology adoption. Consequently, we find that Information Acquisition has a significant positive effect on perceived behavioral control, and Access to Financial Resources has a direct positive effect on Technology Adoption Intention. These findings also provide some insights for policy implications. The effective policies targeting modernization of agriculture should facilitate access to credit and information acquisition for technology and enhance government subsidies.

We also add ‘education level of the farmer’, which is found significant by Rogers et al. (2014), as well as Knight et al. (2003) concerning technology and innovation in agriculture. Education has a significant positive indirect effect on technology adoption through knowledge and information acquisition. This signifies the role of education as a factor that facilitates obtaining information about new technologies supporting Knight et al. (2003).

As a result, producers' investment decisions regarding new technologies in Turkish agriculture are mainly based on access to financial resources. Farmers' both attitudes and subjective norms support the perceived behavioral control in adopting technology; however, this effect is directly manifested through access to financial resources. In addition, information resources strengthen perceived behavioral control, while the level of education supports the processes by facilitating the acquisition of information. In this context, policymakers should primarily develop regulations that will enable small and medium-sized producers to access credit under suitable conditions. Simplifying the process of accessing credit, alleviating collateral demands, and creating flexible repayment plans suitable for harvest cycles will strengthen producers' perception of self-sufficiency and eliminate financial barriers. In addition, expanding workshops integrating financial literacy and technology use training; providing both financial guidance and technology introduction in the field through mobile support teams will increase farmers' competence in investment management and their willingness to adopt new agricultural practices. In terms of acquisition of information, demonstration areas and farmer schools established at the local level should be used together with digital tools to provide concrete examples of the application of technology in the field. Access to technical and economic information should be provided via SMS or mobile applications. Government incentives should be designed with gradual subsidy mechanisms and performance-based reimbursement systems that will support regional early adopter farmers; educational institutions should increase long-term awareness by integrating agricultural technology and financial management into vocational high school curricula. Furthermore, the diversity of participant profiles—including factors such as different age groups, business sizes, and formal education levels—reinforces the need for policy interventions to be tailored. While access to financial resources emerges as a common barrier across groups, the nature and severity of this barrier varies by the socio-economic and demographic characteristics of producers. Therefore, the proposed strategies should be designed with the flexibility to address the diverse needs of farmers. This inclusive approach will ensure that policy recommendations are not only effective at the aggregate level but also respond fairly and sensitively to diverse agricultural contexts. The effectiveness of all these arrangements should be continuously monitored through a monitoring system such as the National Technology Adoption Observatory and improved in light of real-time data. This integrated approach will eliminate financial barriers while strengthening the information and education dimension, enabling producers who not only have access to financing but also have mastered cognitive and social dynamics to effectively adopt new agricultural technologies.

CRediT authorship contribution statement

Emel Mirza: Conceptualization. **Zeki Bayramoğlu:** Writing – review & editing, Methodology. **Hasan Gökhan Doğan:** Data curation, Conceptualization. **Serhan Candemir:** Writing – original draft. **Ali Ganiyusufoğlu:** Writing – original draft, Investigation. **Ayşen Edirneligil:** Writing – original draft, Validation.

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Declaration of competing interest

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Data availability

Data will be made available on request.

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