Understanding the Intention-Behavior Gap: Exploring Behavioral Factors in the Adoption of Climate-Smart Agriculture

Contributed Paper for the 98th Agricultural Economists Society (AES) Conference in Edinburgh Scotland, UK, 18th – 20th March 2024

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Abstract:
Climate-smart agriculture (CSA) addresses the dual challenge of agriculture, yet the interplay of social-psychological and socio-economic factors in farmers' CSA adoption decisions remains unexploited. This study employed the Theory of Planned Behavior (TPB) to investigate the intention-behavior gap in the adoption of CSA. It extended the TPB framework by incorporating additional behavioral, farm business motives, and socio-economic factors. Data from 721 farmers in five European countries were collected and analyzed employing partial least squares structural equation modeling (PLSSEM) and zero-inflated Poisson (ZIP) regression. The original TPB latent constructs—social norm, attitude and perceived behavioral control—positively and consistently influenced adoption intention across non-adopter, practice adopter and technology adopter groups. The findings indicated that perceived CSA compatibility influences adoption intention directly and indirectly, through attitude, in different adopter groups. While CSA ease to use influences adoption intention only indirectly through attitude mediation. Although adoption intention is a significant predictor of actual behavior, the findings reveal that non-economic farm business motives positively influence actual adoption decisions, while economic motives had a negative influence. Moreover, risk tolerance attitude, extent of agricultural training service utilization, age, and farm size were also significant factors influencing CSA adoption decisions. These results conclude that even though behavioral intention drives actual adoption decisions, other factors also play a crucial role in final adoption decision making. Therefore, this study underscores the significance of considering behavioral factors beyond intention and emphasizes towards tailored interventions that consider the specific characteristics of different groups of farmers can be more effective in promoting farmer uptake of CSA.

Introduction

EU has identified and included climate-friendly agricultural practices and technologies as a critical priority for its new Common Agricultural Policy (CAP) (2023-2027) (Runge et al., 2022). Despite EU policies and CSA practices being around, the adoption remains slow and low (Long et al., 2016; Pagliacci et al., 2020). CSA practices and technologies adoption by farmers are complex due to their multidimensional nature incorporating behavioral, technological and social influence linkages (De Lauwere et al., 2022; Giua et al., 2022; Han & Niles, 2023). Recently, more studies have focused on behavioral factors, as socio-economic factors alone do not fully explain adoption behaviors (A. Barnes et al., 2022; De Lauwere et al., 2022; Everest, 2021). The integration of behavioral factors as predictors of sustainable practice adoption is a new contribution to behavioral agriculture economics (Wuepper et al., 2023). It was demonstrated that behavioral factors play a vital role in shaping farmers' adoption decision-making process for sustainable agriculture activities (Dessart et al., 2019). Similarly, non-financial factors also motivate farmers to adopt sustainable farming practices and technology

(Howley, 2015; Trujillo-Barrera et al., 2016). It was indicated that farm business environmental and socio-cultural motives were more important than economic objectives in predicting farmers' adoption of sustainable practices (Kallas et al., 2010).

Gaining a comprehensive understanding of the farmers' behavioral aspects that influence the intention and decision to adopt climate-friendly agricultural practices and technologies on top of socioeconomic factors can offer valuable insights and tools for policymakers to consider when formulating policies (A. Barnes et al., 2022; Doran et al., 2020). It was demonstrated that farmers who had adopted technologies and those who did not adopt had different adoption intentions due to their different expectations for the technologies (Kernecker et al., 2020). In this regard, analyzing adoption intention determinants by categorizing farmers into adopters and non-adopters based on the observed adoption behavior (decision of adoption) can help to fill the gap (Luh et al., 2023). Despite the past research's contribution, there is limited understanding of the behavioral factors that drive adoption intentions at actual adoption decision category levels, even if these factors are recognized as directing individuals' behavior differently (Ajzen, 1991). To uncover this issue, this study attempted to analyze farmers' adoption behavior by clustering farmers by their actual behavior into adopter and non-adopter groups of CSAs.

An increasing amount of research attempts to understand climate change adaption and mitigation practice intention to adopt, but little has examined how the intention to adopt differs from actual adoption (Luh et al., 2023; Niles et al., 2016). It was revealed that intention does not merely turn to the actual behavior indicating an intention-behavior gap (Sheeran, 2002; Sheeran & Webb, 2016). For intention-behavior consistency, individuals with positive intentions subsequently act and individuals with negative intentions do not act (Sheeran, 2002). The gap will occur when individuals do not act according to their intentions, i.e. individuals with positive intentions will fail to act while individuals with negative intentions will perform the behavior (Sheeran, 2002). It is also indicated that farmers who intend to adopt, even with higher intentions, might fail to make an adoption decision due to a range of internal and external factors (Luh et al., 2023; Niles et al., 2016). A recent systematic review by Thompson et al. (2023) on the adoption of ecological practices also indicates that more than 60% of the reviewed studies that applied behavioral models do not capture a common intention-behavior gap. Minimizing the intention-behavior gap requires a more comprehensive understanding of factors and their interplay (Fink et al., 2021). Based on observed and latent factors, this study attempted to bridge the gap between intentions and actual behavior by looking at determinants of adoption intention and actual behavior.

Conceptual and theoretical framework to explain determinants of adoption of CSA

Of the different behavioral change models that were applied in the context of agriculture, the theory of planned behavior (TPB) is the best fit theoretical framework to predict and explain a wide range of farmers' adoption behaviors (Sok et al., 2021). It is modeled by three core components, namely, attitude, subjective norm and perceived behavioral control, which together are assumed to shape an individual's behavioral intentions (Ajzen, 1991). Farmers' attitudes, which are expressed as an evaluation of the positive or negative benefits of adopting CSA, indicate that if farmers consider that adopting CSA will be beneficial, that in turn influences their adoption intention(Daxini et al., 2019; Li et al., 2022, 2023). A subjective norm that captures the extent of social pressure or prospects sensed by a farmer from significant reference groups results in a social complying effect where farmers who tend to follow the norms change their intention to perform pro-environmental behavior (Hüttel et al., 2022; Silvi & Padilla, 2021). Perceived behavioral control refers to an individual' perception of the ease or difficulties related to performing the behavior, which is also a situational constraint related to the availability of resources and skills (Ajzen, 2002).

Even though TPB has a good predictive power towards behavioral change, mere knowledge of the influence of the original TPB constructs on intentions is not always sufficient(Ajzen, 2011). Rather, extending it is highly recommended to capture the complex nature of adoption (Daxini et al., 2018). The literature indicates that compatibility and complexity influence the intention to adopt a technology(Moons et al., 2022). They also directly influence individual attitudes toward technology adoption(Kaine & Wright, 2022; Serebrennikov et al., 2020), thus indicating the mediation effect of these two factors. As a result, the compatibility and ease to use of CSA were explored as TPB extension constructs for predicting CSA adoption intention.

Adoption intention and perceived behavioral control are prominent predictors of actual behaviors (Ajzen, 1991). TPB asserts that behavioral achievement relies on motivation to engage in a behavior (Ajzen, 1991, 2011). Despite evidence that social-psychological and socio-economic factors influence farmer decision-making, farmers farm business motives like economic, non-economic, and risk tolerance attitudes determine adoption decisions(Castro Campos, 2022; Howley, 2015; Nainggolan et al., 2023; Trujillo-Barrera et al., 2016); as a result, they were considered predictors for actual CSA adoption decision. Furthermore, the extent of using information sources, including agricultural training and advisory services sources has a predictive power for adoption decisions by providing knowledge and skills about implementing CSA (Caffaro et al., 2020; Giua et al., 2022). Finally, to account for variations that come from observed factors, namely farmer age, farm size, income level, educational level and farmers' cooperative membership status, they are indicated as determinants of adoption decisions (Kernecker et al., 2020). Based on theoretical evidence, this study employed a conceptual framework in Figure 1 to explain farmers' CSA adoption intention and actual decision.

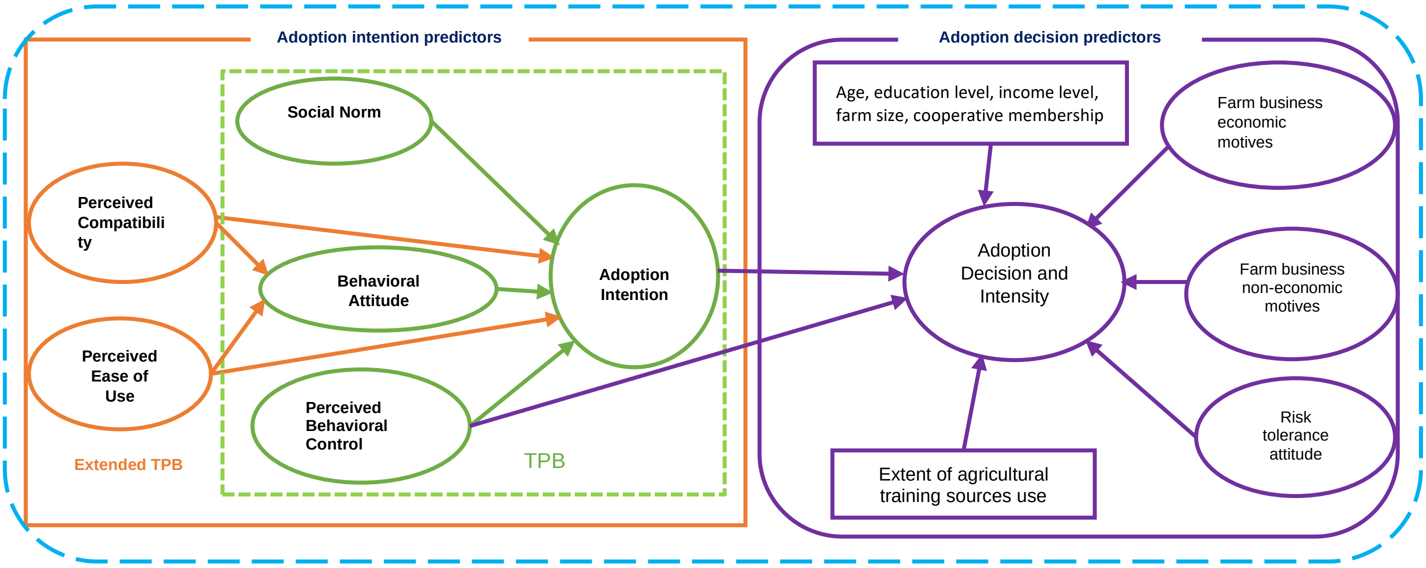

Figure 1. Conceptual and theoretical framework for CSA practice and technology adoption prediction.

Research Methodology

Description of data

The survey data were collected between January and March of 2023 across five European countries (i.e., Denmark, the Netherlands, Spain, Lithuania and Slovenia). The questionnaire was formulated in English and subsequently translated into local languages. Behavioral Change Towards Climate-Smart Agriculture (BEATLES) project's use cases (UC) in each nation distributed the survey link via agricultural institutional networks, farmer associations, and their social network media. A total of 721 farmers filled out the online survey. The survey included questions involving individual, technological and social influence-related decision-making factors for adoption of CSA practices and technologies. The survey started with a brief description of what CSA is by provided some examples of CSA practices and smart farming technologies. It questions whether farmers know what CSA is and whether they have implemented CSA practices in the past five years. This question was followed by questions requesting farmers to describe the CSA practices and technologies they are currently implementing. For the items of questions, seven Likert scales were used to capture latent behavioral factors. Furthermore, items questions focusing on the extent of using agricultural training services sources were included. Finally, questions about socioeconomic characteristics were included.

Data analysis framework

First based on farmers' responses to the CSA description, farmers were categorized into three groups: practice adopters, technology adopters and non-adopters. Adoption can be seen as a binary variable that serves to encode the decision to adopt-in this case (Ferrer et al., 2023; Giua et al., 2022). Accordingly, farmers who described using CSA practices and technologies for the last five years and implementing them currently were considered adopters otherwise non-adopters. Alternatively, adoption can be represented by the cumulative adoption of several practices and technologies, thereby indicating the intensity of adoption for each observation (Giua et al., 2022; Thompson et al., 2022).

Behavioral factors are not directly observable, but there are measurable indicators of these factors that are observable and can be used to assess the latent constructs (DeVellis & Thorpe, 2021). The causal relationship between the latent construct and the observable measurement indicators is an important consideration when measuring latent constructs (Rossiter, 2002). The underlying theory should be the main consideration in determining whether the formative or reflective model is chosen (Coltman et al., 2008). A formative model should be employed if it is considered that the indicators are the cause of the latent construct, while in the case of the reflective model, the latent construct is assumed to be the cause of the indicators (Coltman et al., 2008). In this study, the underlying constructs are deemed the cause of the measurement indicators; thereby, a reflective model was considered. To examine the causality relationship between the constructs and other factors, three estimation approaches were employed to validate the proposed hypotheses with the aid of STATA 17 and R version 4.2.3.

The first approach was predicting the proposed TPB constructs on adoption intention. As the aim of this study is to predict and identify key target constructs, Partial least squares structural equation modeling (PLSSEM) was preferred (Hair et al., 2011; Ringle et al., 2023). Due to the nature of heterogeneity in adoption behavior, a multigroup PLSSEM approach was followed to assess whether the relationships differ across different groups (non-adopters, CSA-practice adopters and CSA-technology adopters) (Ren & Zhong, 2022). The PLSSEM approach involves two stages. First, the measurement model to empirically evaluate the individual and composite reliabilities of their indicators and reliability statistics such as factor loading, Cronbach alpha, and average variance extracted were examined to evaluate the constructs' reliability (Coltman et al., 2008). Following the reflective model satisfactory criteria evaluation, in the second part of PLSSEM, the structural model analyses the relationships among the latent factors and the outcomes to draw inferences on the hypothesized relationships. Assuming the latent constructs as: η_{att}, η_{sn}, η_{pbc}, η_{peu}, η_{pc} *and* ξ_{int} representing attitude, social norm, perceived behavioral control, perceived ease to use, perceived compatibility and adoption intention, respectively, the structural model specified as:

$$\xi_{int} = \beta_{att}\eta_{att} + \beta_{sn}\eta_{sn} + \beta_{pbc}\eta_{pbc} + \beta_{peu}\eta_{peu} + \beta_{pc}\eta_{pc} + \epsilon_{int} \qquad (1)$$

Where $\beta's$ is the direct path coefficient for proposed constructs and ϵ_{int} *is* error term for the adoption intention construct.

However, as indicated in the conceptual framework, there is an indirect relationship between attitudes, perceived compatibility, and perceived ease of use. Accordingly, the second procedure structural model of PLSSEM is estimating the relationship between the latent variables to account for mediation. Accordingly, considering the effect of perceived ease of use (η_{peu}) and perceived compatibility (η_{pc}) on the attitude (η_{att}) construct as a mediation, the following structural model is specified:

$$\eta_{att} = \gamma_{peu}\eta_{peu} + \gamma_{pc}\eta_{pc} + \epsilon_{att} \quad \text{......(2)}$$

Where γ_{peu} and γ_{pc} the path coefficients of η_{peu} and η_{pc}, respectively.

Finally, the direct and indirect influence of two endogenous constructs and the direct influence of three exogenous constructs on the adoption intention is specified:

$$\xi_{int} = \beta_{att}\eta_{att} + \beta_{sn}\eta_{sn} + \beta_{pbc}\eta_{pbc} + \beta_{peu}\eta_{peu} + \beta_{pc}\eta_{pc} + \gamma_{peu}\eta_{peu}\eta_{att} + \gamma_{pc}\eta_{pc}\eta_{att} + \epsilon_{int} \quad \text{.....(3)}$$

Where $\gamma_{peu}\eta_{peu}\eta_{att}$ and $\gamma_{pc}\eta_{pc}\eta_{att}$ represent the indirect influence of η_{peu} and η_{pc} on ξ_{int}, respectively.

To test the mediation effect, *the medsem* Stata package by Mehmetoglu (2018) was employed, as it follows Baron & Kenny (1986) and Zhao et al. (2010) bootstrapping mediation testing approaches.

The second approach for this study involved an explanatory factor analysis to generate construct scores for anticipated latent factors used as actual adoption predictors. Accordingly, factor analysis for indicators of anticipated factors was analyzed. Because anticipated factors likely correlate, oblique rotation was employed to facilitate the interpretation of the factors and rotate the factor solution (J. Hair et al., 2010; Watkins, 2018).

The final approach is an analysis of the influence of the anticipated latent factors from explanatory analysis and hypothesized socioeconomic variables on actual adoption. As a significant portion of our sample consists of non-adopters, which leads to an overrepresentation of zero values, this study employed a Zero-inflated Poisson (ZIP) model to predict the influence of decision-making factors on both adopting and not adopting CSA and, at the same time, on the intensity of adopting CSA. The predicted count outcome(Y_i), with x_i as a vector of explanatory variables, can be expressed as:

$$\Pr\,(Y_i = y_i x_i) = \begin{cases} \psi_i + (1-\psi_i)\exp(-\mu_i) & if\ y_i = 0 \\ (1-\psi_i)\frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} & if\ y_i > 0 \end{cases} \quad \text{......(4)}$$

Where ψ_i is the likelihood of the logistic distribution. ZIP consists of two components: A zero-inflation model, which is binomial with a logit link for non-adopters, explains the threshold between non-adoption and CSA adoption intensity, while a count model, which is Poisson with a log link for those adopting the technology, explains the factors influencing the adoption intensity of CSAs.

Result and Discussions

Behavioral determinants of CSA adoption intention

As the first step in the evaluation of PLSSEM reflective measurement model, the loading of indicators that account for indicator variance demonstrates an adequate level of item reliability exceeding 0.708(Sarstedt et al., 2021). Secondly, the constructs' internal consistency reliability is assessed based on the composite reliability, in which results between 0.70 and 0.95 represent satisfactory to good reliability (Hair et al., 2021; Sarstedt et al., 2021). Furthermore, Cronbach's alpha was assessed as a measure for internal consistency reliability, which indicated good consistency indicators[1] as its value is greater than 0.8 (Sarstedt et al., 2021). For convergent validity assessment, average variance extracted(AVE) was employed to measure how well a construct explains the items' variation (Valizadeh et al., 2023) and confirmed convergent validity as it was greater than 0.50 (Sarstedt et al., 2021). Finally, the assessment of discriminant validity confirmed that each latent construct loading was greater than its cross-loadings (Hair et al., 2021; Sarstedt et al., 2021). Satisfactory quality of measurement model, structural model assessment for path coefficient significance and predictive power based on a coefficient of determination (R^2) value of 0.67 for a pooled sample and greater than 0.65 for multi-groups indicate good predictive ability (Sarstedt et al., 2021).

Table 1 results in the column corresponding to the pooled sample indicate that the basic TPB constructs, and perceived compatibility have a significant influence on the adoption intention of CSA. It also indicates that the two hypothesized extension constructs have a significant influence on the farmer's attitude towards CSA. The mediation test result shows that perceived ease to use has complete mediation, indicating that it has a significant indirect effect on adoption intention but an insignificant direct effect on adoption intention. Likewise, the mediation test for perceived compatibility of CSA practices and technologies confirms that it has partial mediation, indicating that it has a significant direct and indirect influence on adoption intention. The column focusing on non-adopters indicates that the basic TPB constructs have a significant influence on adoption intention, while the TPB extension constructs are not significant. It also indicates that the two extension constructs have a significant influence on the farmer's attitude towards CSA. The mediation test confirmed that the extension constructs have a significant and positive indirect influence on adoption intention, besides their insignificant direct influence. The column focusing on CSA-practice adopters also showed the basic TPB constructs have significant influences of adoption intention. It also confirmed that the proposed TPB extension constructs have a significant influence on CSA implementation attitude, besides their insignificant direct influence on adoption intention. The mediation test confirmed the TBP extension constructs have a positive and significant indirect influence on adoption intention. The final column focusing on CSA-technology adopters indicates that perceived behavioral control, social norms, and perceived compatibility have a positive influence on adoption intention and only perceived compatibility has a significant positive influence on attitudes towards CSA-technology. The mediation test confirmed that only perceived compatibility influences the adoption intention of CSA-technologies positively and significantly, both directly and indirectly through farmers' attitude.

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[1] Indictor statements for CSAatt, Snorm, Comp, Peas and refer Table 2 for Intent, PBC indicator statements.
*Attitude towards technology (CSAatt): If I am going to adopt climate smart agricultural practices and technologies, I think that it will: [lower production costs, increase productivity, reduce workload, be useful for farm operations].
**Social norm (Snorm): Many farmers in my surroundings apply a CSA, Farmers similar to me mostly use a CSA, People, who's opinion I value, think that I should apply a CSA, People, who are important to me, would approve the use of a CSA
***Perceived Compatibility (Comp): If I am going to adopt the climate-smart agriculture practice/technology, I think that it will: [suit in the way I like to work, be consistent with the goals I find relevant]
****Perceived ease of use (Peas): If I am going to adopt the climate-smart agriculture practice/technology, I think that it will: [be easy to learn; be easy to control; be easy to understand how it is used]

Table 1: PLSSEM multi-group analysis result

Constructs	CSA practices and technologies adoption intention			
	Pooled sample	**Non-adopter**	**CSA-practice adopter**	**CSA-technology adopter**
	Coefficient	Coefficient	Coefficient	Coefficient
PBC->Intent	0.450 (0.000)	0.319 (0.000)	0.607 (0.000)	0.315 (0.000)
CSAatt-> Intent	0.186 (0.000)	0.261 (0.000)	0.244 (0.002)	0.291 (0.001)
Snorm-> Intent	0.157 (0.000)	0.116 (0.09)	0.149 (0.006)	0.142 (0.008)
Comp-> Intent	0.109 (0.017)	0.084 (0.225)	0.124 (0.091)	0.208 (0.044)
Peas-> Intent	0.073 (0.081)	0.123 (0.061)	-0.093 (0.228)	0.027 (0.737)
R^2	***0.671***	***0.668***	***0.688***	***0.691***
Attitude towards CSA implementation				
Comp-> CSAatt	0.536 (0.000)	0.470 (0.000)	0.383 (0.000)	0.759 (0.000)
Peas-> CSAatt	0.308 (0.000)	0.365 (0.000)	0.480 (0.000)	0.101 (0.152)
R^2	***0.637***	***0.617***	***0.634***	***0.584***
Indirect influence on adoption intention				
Comp-> CSAatt-> Intent	Partial mediation	Complete mediation	Complete mediation	Partial mediation.
Peas-> CSAatt-> Intent	Complete mediation	Complete mediation	Complete mediation	No mediation.

Note: *P-values in parentheses, group sizes: Non-adopter: 374, CSA-practice adopter: 171, CSA-technology adopter: 176 with a pooled sample size of 721*

Intent=adoption intention, PBC=perceived behavioral control, CSAatt= attitude towards CSA, Snorm=social norms, Comp=perceived compatibility, Peas=perceived ease of use ; Indirect influence was estimated by following the Baron & Kenny (1986) and Zhao et al. (2010) bootstrapping mediation effect estimation approach.

Determinants for actual adoption decision and intensity of CSA

Latent factors scores that represent the underlying factor of interest from indicator statements are needed to estimate the proposed actual adoption behavior predictors by following Zero Inflated Poisson (ZIP) model. Based on oblique rotation factor analysis, factor loadings above 0.30, which represents statistical significance at the 5% level were considered (Hair et al., 2010; Sarstedt et al., 2021). Table 2 displays the outcomes of the explanatory factor analysis. Factor loadings that were rotated for all six factors showed that a factor solution had been maintained. Three indicator statements that had rotational factor loadings < 0.3 were excluded from the final factor analysis[b]. In the final stage of factor analysis, according to Kaiser's overall measure of sampling adequacy (KMO), all of the Cronbach's alpha values were higher than the threshold value of 0.7, indicating that statements had a satisfactory factor solution (J. Hair et al., 2010).

Table 2: Factor analysis to reduce the dimensionality of factors.

Factors	Statements	Rotated factor loadings	Unique ness	Scoring coefficients
Adoption intention (Intent)	I plan to adopt a climate-smart agriculture practice or technology	0.7849	0.2585	0.32682
	I will regularly try to apply a climate-smart agriculture practice or technology in the near future	0.8232	0.2401	0.36759
	If it were entirely up to me, I am confident that I will adopt a climate-smart agriculture practice or technology	0.7521	0.3145	0.30289
Perceived behavioural control (PBC)	I have the ability to implement a CSA	0.6800	0.3752	0.33334
	If it were entirely up to me, I am confident that I will adopt a CSA	0.5488	0.4624	0.22395
	I have the resources, time, and willingness to apply a CSA on my farming activities	0.6596	0.4780	0.25199
Farm business nonpecuniary motive (NonEcoMot)	It is important to me that running my farm business I prefer to produce in an environmental-friendly way	0.8227	0.3053	0.31333
	It is important to me that running my farm business I prefer to produce with care for animal welfare	0.7578	0.3208	0.27764
	It is important to me that running my farm business I prefer to produce with care for public health	0.7445	0.3438	0.23493
	It is important to me that running my farm business I prefer to produces fairly priced products	0.8020	0.4654	0.17283
Farm business Economic motives (EcoMot)	It is important to me that running my farm business results in high yields	0.6917	0.5107	0.35361
	It is important to me that running my farm business results in a high income	0.6783	0.5736	0.31243
	It is important to me that running my farm business has low production costs	0.4615	0.6057	0.23150
	It is important to me that running my farm business produces the highest quality products	0.4455	0.6354	0.11886
Risk tolerance attitude (RiskTol)	When I take decisions concerning my farming business, I prefer certainty over uncertainty	0.6509	0.4814	0.40482
	When I take decisions concerning my farming business, I avoid risks in my investments	0.6778	0.5583	0.34420
	When I take decisions concerning my farming business, I like to take financial risks(reversed)	0.3740	0.7106	0.19699
Extent of agricultural training services sources use (ExtentAgrTrain)	To what extent did you make use farmer trainings as service source for your agricultural training in the last five years?	0.6392	0.5554	0.11110
	To what extent did you make use farm visits as service source for your agricultural training in the last five years?	0.7974	0.3300	0.22776
	To what extent did you make use field demonstrations as service source for your agricultural training in the last five years?	0.8119	0.2224	0.35322
	To what extent did you make use field/farmers days as service source for your agricultural training in the last five years?	0.7571	0.3213	0.22415
	To what extent did you make use workshops/open discussions as service source for your agricultural training in the last five years?	0.7084	0.4995	0.14248
	To what extent did you make use advisory services as service source for your agricultural training in the last five years?	0.6589	0.5995	0.10374

[b]**Note: The following statements were removed from final factor analysis due their low factor loading (below 0.3)** (Sarstedt et al., 2021)
It is important to me that running my farm business has a low labour need (economic motive factor category)
It is important to me that running my farm business maintains the tradition of my family (farm business noneconomic motive factor category).
It is important to me that running my farm business is good for the employment in my rural area (farm business *economic motive factor category)*

The likelihood ratio test (LRT) was employed for comparing a ZIP with an alternative zero-inflated negative binomial (ZINB) model: ZIP LogLik =-650.9, df=36, and ZINB LogLik=-649.52, df=36 with p value Pr(>X^2) =0.9984 indicates that the ZIP model is preferable and sufficient. For complex models, including ZIP and ZINB models, R^2 may not have a clear interpretation (Martin & Hall, 2016). Thus, alternative measures like the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are suggested to assess model fit (Minami et al., 2007), where lower values indicate better model fit. Our data shows that for ZIP, the AIC is 1283.031 and the BIC is 1425.848, while for ZINB, the AIC is 1285.031 and the BIC is 1432.311, indicating ZIP's better model fit. Table 3 for the ZIP model's results shows raw coefficient estimates (β) and odds ratios (exp(β)), where the discussion focused on odds ratios as these provide indications of the likelihood of factors (Barnes et al., 2019). ZIP's Poisson link function output that provides coefficients that represent the log of the expected count (intensity) of CSA adoption and binomial logit link functions for the non-adoption model are presented below.

Actual adoption by current adopters.

The ZIP count model with a Poisson link function result (Tabel 3) shows that adoption intention, farm businesses non-economic motives and extent of agricultural training services used have a significant and positive influence on the intensity of CSA adoption. Farm business economic motives and risk tolerance attitudes of farmers have significant and negative effects. Regarding socioeconomic factors, the elder age group of farmers have the lower adoption intensity of CSA compared to younger ones. Large farm-size holding farmers have a higher adoption intensity as compared to lower farm size holding.

The positive influence of intention on CSA adoption intensity is confirmed by a significant odds ratio value of higher than one, indicating that farmers agree with adoption intention statements. This would seem to agree with several studies that confirmed that higher adoption intentions will lead to greater likelihood of making adoption decisions (Bagheri et al., 2019; Bonke & Musshoff, 2020; Li et al., 2020). As indicated by Ajzen (1991), behavioral intention can affect actual behavior only if the behavior in question is under volitional control. This confirms that CSA adoption behavior is in line with, but still depends on other farm business motives, perceived resources, skills and confidence for the implementation, as well as socioeconomic factors. In this study, farmers perceived behavioral control (PBC) did not have a significant effect on actual adoption behavior even though it has a positive effect on their intensity to adopt. In this regard, the results from previous studies are mixed; for instance, Bonke & Musshoff (2020) and Li et al. (2020) found an insignificant effect of PBC on actual behavior. In contrast, studies by Bagheri et al. (2019) found PBC's significant effect on actual adoption. As hypothesized, non-economic farm business motive is significant and positive, indicating that farmers with higher non-pecuniary farm business motives have a higher probability of adopting CSA. The odds value from ZIP regression is greater than one, indicating that farmers are more in agreement with the proposed statements, to make the adoption decision more likely. This was confirmed by Howley (2015) indicated that farmers with higher non-peculiarly farm orientation behavior have a higher likelihood of implementing sustainable agricultural practices. Thompson et al. (2022) also indicate farmers with non-economic environmental farm business objectives have a positive influence on the adoption intensity of sustainable agricultural practices in Europe.

Similarly, the odds of the model result for farmers' economic farming business motives are nearly one, indicating that farmers who are more in agreement with given statements are less likely to adopt a greater number of CSA. This may be due to the high cost of CSA implementation (Long et al., 2016), which could have a higher impact on the economic orientation of farm businesses and in turn influence adoption decisions (Thompson et al., 2023). Previous research findings also confirm that farmers' increased productivity objectives will lower the likelihood of adoption intensity for sustainable agricultural practices (Thompson et al., 2022). This result disagrees with the finding of Trujillo-Barrera et al.(2016), that found economic motives to have a positive influence on the decision to invest in certified stables. Likewise, other previous studies found insignificant results on the effect of financial goals on the adoption of sustainable practices (Degieter et al., 2023). With this mix of findings, we argue that the findings of this study are in line with CSA adoption, as investing in CSA practices and technologies has some additional costs that compromise the farmer's profitability, which in turn influences the farmer's adoption decision and intensity of adoption. In this regard, incentives to compensate the farmers could enhance adoption (Pagliacci et al., 2020).

The extent of using different agricultural training services has a positive effect on CSA adoption intensity. The odds value of greater than one for the factor indicates that farmers agree with the statements, implying its significant supporting impact. This suggests that field days, extension training, exhibitions, open discussion, and advisor services may help fill the CSA implementation knowledge gap and encourage adoption, which is also confirmed by previous studies (Barnes et al., 2019). Of the socioeconomic factors included, the age of respondents has a negative effect on the adoption intensity of CSA. Farmers with ages 40-50 and >= 51 years are less likely to adopt CSA as compared to farmers with ages <=39 years. A similar result was shown by Rodríguez-Barillas et al. (2024). Adoption of CSA is also influenced by farm size, as the ZIP model indicated that farmers with larger farm sizes have a higher CSA adoption intensity. This was reflected in the fact that the odds of farmers' CSA adoption intensity are greater for farmers with farm sizes of 51–100 and >100 hectares as compared to farmers in the farm size group <=10 hectares, which is also in line with Degieter et al. (2023).

Adoption decisions by current non-adopters.

The result of ZIP with a binomial logit link for the non-adopter (Tabel 3) shows that adoption intention, perceived behavioral control, risk tolerance attitude and extent of agricultural training service use are significant factors influencing the likelihood of CSA non-adoption. The odds value of adoption intention is less than one, indicating that farmers are not as in agreement regarding the statement effects of the non-adoption of CSA. While the odds of farmers' risk tolerance attitude increase the likelihood of not adopting CSA. Its odds ratios are greater than one, indicating that farmers in strong agreement with the statements would tend towards non-adoption. The perceived behavioral control does not support the likelihood of not adopting CSA, as confirmed by its negative and significant influence on non-adoption. Moreover, the extent of use of diversified agricultural training and advisory sources demonstrate negative and significant effects on non-adopting CSA. Of the socioeconomic factors, farmers over the age of 50 have increased odds of not adopting CSAs as compared to the younger age group. The odds ratios for larger farm sizes confirm that farmers adopt more CSA practices and technologies, whereas large farms have lower likelihood of being non-adopters compared to farmers with smaller farms. This is supported by previous studies showing that farmers with larger farms are more likely to adopt smart farming technologies (Barnes et al., 2019; Giua et al., 2022). The likelihood of not adopting CSA is also significantly influenced by higher education and income groups, compared to lower levels of education and higher income.

Table 3: Zero-Inflated Poisson Regression Model Result for Predictors of CSA Adoption Intensity

Predictors	Count model coefficients (Poisson with log link)				Zero-inflation model coefficients (Binomial with logit link)			
	Estimate	odds ratios (exp(β))	Std. errs.	Pr(>|z|)	Estimate	odds ratios (exp(β))	Std. errs.	P>z
Intention	0.24128	1.272880e+00	0.09951	0.015320 *	-1.7897	1.670143e-01	0.5920	0.0025 **
PBC	0.06195	1.063906e+00	0.09680	0.522193	-2.8161	5.986248e-02	1.0277	0.0096 **
NonEcoMot	0.19880	1.219942e+00	0.07028	0.004672 **	0.4357	1.546105e+00	0.4521	0.3351
EcoMot	- 0.12573	8.818541e-01	0.04282	0.003325 **	0.4131	1.511466e+00	0.3022	0.1717
RiskTol	-0.06024	9.415345e-01	0.05404	0.264930	0.3187	1.375012e+00	0.1497	0.044*
ExtentAgrTrain	0.15404	1.166536e+00	0.06069	0.011140 *	-0.8988	4.070564e-01	0.4319	0.0374 *
Age_group2(40-50years)	-0.44053	6.436945e-01	0.11965	0.000232 ***	19.1655	2.105993e+08	356.6371	0.9960
Age_group3(>=50years)	-0.15567	8.558378e-01	0.13536	0.250114	22.5887	6.458668e+09	385.6705	0.9953
Inco_group2(EUR50.001-100.0)	0.13270	1.141903e+00	0.15291	0.385502	2.6956	1.481380e+01	1.3889	0.0523 *
Income_group3(>=EUR100.001)	0.24440	1.276859e+00	0.15745	0.120610	2.0538	7.797557e+00	1.2597	0.1030
Farmsz_group2(51-100ha)	0.38183	1.464966e+00	0.13049	0.003433 **	-1.7358	1.762599e-01	0.7899	0.0280 *
Farmsz_group3(>100ha)	0.29411	1.341927e+00	0.12619	0.019767 *	-2.2037	1.103968e-01	0.9676	0.0228 *
Educ_group2(vocational_training)	-0.01180	9.882663e-01	0.15082	0.937620	-0.3723	6.891746e-01	1.2105	0.7584
Educ_group3(bachelor & above)	0.14161	1.152132e+00	0.12658	0.263251	0.8233	2.277994e+00	0.8737	0.3461
Coop.membership (yes)	0.23885	1.269788e+00	0.10049	0.017462 *	-0.1905	8.265733e-01	0.6414	0.7665
Country(group2)	0.38264	1.466146e+00	0.13199	0.003745 **	2.0168	7.513945e+00	0.9881	0.0412 *
Country(group3)	-0.07415	9.285324e-01	0.13733	0.589242	0.5660	1.761258e+00	1.0396	0.5861
Intercept	-0.56078	5.707622e-01	0.19719	0.004457 **	-24.4113	2.502078e-11	386.6776	0.9949

Note: *Age_group 1(<39years), Farmsiz_ group1(<50ha), Educ_group1(secondary_school), Income_group1(<EUR50.000) and* Country(group1) *are base categories*

Concluding remarks

This study highlights the intention-behavior gap in the adoption of CSA. It showed that basic TPB constructs and TPB extension, perceived compatibility, significantly influence adoption intention. The study also shows that perceived compatibility and ease to use of CSA influence farmers' attitudes, with indirect effects of perceived ease to use and compatibility on adoption intentions. Interestingly, the mediation tests showed that perceived ease of use had a complete mediation effect, meaning it had a large indirect effect on adoption intention but a small direct effect. However, the perceived compatibility of CSA techniques and technologies partially mediated adoption intention, showing a strong direct and indirect effect. The multigroup SEM analysis results provide valuable insights into the nuanced factors influencing the adoption intentions of farmers across different groups—non-adopters, CSA-practice adopters, and technology adopters.

The factors influencing the actual adoption behaviour of CSA show that intention is a major predictor of CSA adoption, but other aspects are too. As external variables can prevent intention from becoming action, considering other factors fills the gap. For instance, non-economic motives positively influenced the adoption decision, demonstrating farmers with a higher orientation towards non-pecuniary motives are more likely to implement CSA. However, farm business economic motives negatively influenced adoption decisions, suggesting that farmers prioritising money are less likely to implement CSA. The finding also demonstrated that risk-tolerant farmers had lower adoption intensity. The extent of using agricultural training service sources positively affected adoption decisions and intensity, suggesting that accessing multiple knowledge sources can stimulate adoption. It is important to note that the results of this study are based on the data and methodology employed, and further research, especially behavioural economic experiments, is needed to validate and expand these findings. Nonetheless, the study contributes to our understanding of the intention-behavior gap by incorporating a range of predictors and exploring the role of other factors in CSA adoption rather than relying on adoption intention alone.

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