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Investigating the relationship between knowledge and the adoption of sustainable agricultural practices: The case of Dutch arable farmers

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ABSTRACT

The intensive usage of synthetic fertilisers and pesticides helps Dutch arable farmers to secure high yields at low costs. However, this intensive arable production system also results in environmental degradation in terms of biodiversity loss and reduced soil and water quality. Adopting sustainable agricultural practices (SAPs) reduces arable farmers' reliance on fertilisers and pesticides. Therefore, SAPs contribute to enhancing farm sustainability and resilience. Despite the promising potential of SAPs, their adoption rates remain low. We investigate which combinations of SAPs are jointly adopted in portfolios and how the adoption rate of SAP portfolios can be improved. Specifically, this paper aims to explore the relationship between knowledge and the adoption of SAP portfolios. First, we investigate the SAP portfolios that are jointly adopted using Correlation Explanation. Second, we estimate a multivariate probit model to explore if SAP portfolios are complementary or substitutionary to each other. Finally, we run a partial least squares structural equation model to investigate how the level of knowledge and informal knowledge are associated with the adoption of SAP portfolios. Results show that both the level of knowledge and informal knowledge are positively related to the adoption of these SAPs that require initial investments or aim to reduce pesticide and fertiliser usage. However, we find no significant relationship between knowledge and the adoption of SAPs that are already subsidised by policymakers. We conclude that persuading farmers to adopt more SAPs requires policymakers to consider combinations of economic (e.g. subsidies) and behavioural policy interventions (e.g. facilitating peer-to-peer knowledge sharing).

1. Introduction

Dutch arable farmers are characterised by their intensive usage of synthetic fertilizers, pesticides, and other plant protection materials (van Grinsven et al., 2019). While this secures high yields and low costs, it comes at the price of environmental degradation in terms of biodiversity loss and reduced soil and water quality (Pe'er et al., 2020). Reversing this trend of environmental degradation requires farmers to reduce their fertiliser and pesticide usage. This is also highlighted in the European Union's Common Agricultural Policy (CAP), as a focal policy goal is a 20% reduction in fertiliser and a 50% reduction in pesticide usage (European Commission, 2020). The adoption of sustainable agricultural practices (SAPs) has the potential to reduce farmers' reliance on fertilisers and pesticides while maintaining current production levels (Piñeiro et al., 2020). Therefore, SAPs have the potential to contribute to farm resilience and sustainability (Meuwissen et al., 2019; Rockstrom et al., 2017).

We define SAPs as practices with beneficial environmental effects on biodiversity, water, soil, landscape, and/or climate change compared to conventional farming practices (adapted from Dessart et al., 2019). Additionally, the Food and Agricultural Organization (FAO) described five features of SAPs: technically appropriate, environmentally non-degrading, resource conserving, economically viable, and socially acceptable (FAO, 1989). Examples include conservation tillage practices, cover crops, agroforestry, and improved water management. Due to recent technological developments and innovations, farmers now have access to a wide range of SAPs. In line with these developments, Weltin et al. (2018) and Dicks et al. (2019) recommend adopting a holistic approach when studying SAPs. Such holistic approaches consider how multiple SAPs are jointly adopted in portfolios. Although SAPs have been popularised and advocated by policymakers, their adoption rates remain low. This raises the question of how farmers can be persuaded to

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adopt combinations of SAPs in a portfolio. Besides being driven by economic and environmental factors, the decision to adopt combinations of SAPs also involves behavioural drivers (Baumgart-Getz et al., 2012; Bopp et al., 2019; Spiegal et al., 2018). One of these key behavioural drivers is a farmer's knowledge of SAPs. Knowledge about the existence of SAPs is required to adopt such practices (Dessart et al., 2019). It can be understood as the existing level of knowledge or how farmers obtain and share knowledge—i.e. either informal or formal knowledge sharing. The objective of this paper is to investigate how knowledge is associated with the adoption of SAP portfolios.

Several theories have been applied to empirically investigate farmers' adoption behaviour, such as the theory of planned behaviour (Ajzen, 1991) and the reasoned action approach (Fishbein and Ajzen, 2011). However, these theories do not explicitly capture how knowledge transfer influences adoption decisions. Other theories acknowledge the importance of knowledge in understanding innovation adoption decisions, such as the diffusion of innovations theory (Rogers, 1962) or the behaviour change wheel (Michie et al., 2011). Underlining the importance of knowledge in adoption decisions, Tensi et al. (2022) recommend farmers and advisors become more active in knowledge sharing to increase adoption rates of microbial products among Dutch and German arable farmers. Other studies confirmed how acquiring knowledge persuades farmers to adopt a specific SAP, such as conservation tillage practices (D'Emden et al., 2008), convert to organic farming (Kallas et al., 2010; Läpple and Rensburg, 2011), and participate in agri-environmental policy schemes (Pavlis et al., 2016).

While these studies provide valuable insights into how knowledge stimulates farmers to adopt individual SAPs, they are silent about how the adoption of combinations of SAPs can be supported by improved knowledge transfer. There are only a few studies that used portfolio approaches to study SAPs. Most of these studies were conducted in developing countries (e.g. Bopp et al., 2019; Kassie et al., 2015). A notable exception is Weltin et al. (2021), who studied German farmers' adoption of sustainable intensification portfolios. They investigated several behavioural drivers of farmers' intention to adopt these portfolios, including attitudes, values, and perceived benefits. However, Weltin et al. (2021) did not consider how knowledge influences the adoption of SAP portfolios.

This study has a threefold contribution. The first contribution is that we provide novel insights into the relationship between knowledge and the adoption of SAP portfolios. We distinguish between farmers' level of knowledge and how farmers acquire informal knowledge by exploiting their social network and capital. Previous studies on the relationship between knowledge and SAP adoption focused on single SAP and did not consider SAP portfolios. The second contribution is methodological. We adjust the three-stage approach proposed by Weltin et al. (2021) to the context of Dutch arable farmers. First, we investigate which SAPs are often simultaneously adopted based on an unsupervised machine learning algorithm. Our methodological contribution is this adjusted first stage, where we apply correlation explanation (CorEx) (Ver Steeg and Galstyan, 2014), which lets the data speak to endogenously identify SAP portfolios. Rather than relying on pre-defined combinations of SAPs to construct portfolios, we investigate the adopted combinations of SAPs. Second, we assess whether the SAP portfolios are complements or substitutes based on a multivariate probit model. Third, we explore how knowledge is associated with farmers' portfolio adoption decisions using a partial least squares structural equation model. The third contribution is our application to Dutch arable farmers. To the best of our knowledge, this is the first case study focusing on Dutch arable farmers. These farmers are a suitable population to study SAP portfolios, as the Dutch arable production system is characterised as intensive and is subject to pesticide and fertiliser overapplication. Hence, adopting SAPs can lower farmers' reliance on pesticides and fertilisers.

Our results are valuable to European policymakers interested in enhancing farm sustainability and resilience. We find that the level of knowledge and informal knowledge are heterogeneously associated with the adoption of SAP portfolios. This suggests that informing farmers about SAP portfolios is helpful to stimulate the adoption of most SAP portfolios, but that other incentives, such as subsidies, remain important as well to boost SAP adoption. Hence, we recommend policymakers combine economic and behavioural interventions.

2. Conceptual framework

Our conceptual framework explains the relationship between knowledge and the adoption of SAP portfolios. We conceptualise SAP portfolios as combinations of jointly adopted SAPs. We construct several SAP portfolios, as there is a wide range of possible SAPs that can be adopted by one or more farmers (Fig. 1). Each portfolio reflects different environmental benefits (Weltin et al., 2021). Complementary or substitutional relationships could exist among different SAP portfolios (Kassie et al., 2015). A complementary relationship means that adopting more SAPs in a portfolio is positively related to the adoption of more SAPs in another portfolio, while substitutional relationships imply that adopting more SAPs in a portfolio comes at the cost of adopting fewer SAPs in other portfolios.

There are several factors influencing farmers' decisions to adopt SAPs, ranging from farm(er) characteristics, economic and environmental characteristics of SAPs, exogenous factors—i.e. off-farm influences—and behavioural factors (Fielding et al., 2008; Foguesatto et al., 2020; Rodriguez et al., 2008). Our conceptual framework builds on a recent literature review on the behavioural factors shaping farmers' adoption decisions (Dessart et al., 2019). In this review, three categories of behavioural factors were identified: cognitive, social, and dispositional factors. We focus on cognitive factors because these factors are most proximal to the farmer and most directly influence adoption decisions. For instance, Massfeller et al. (2022) found that cognitive factors were positively associated with the likelihood of adopting sustainable practices. Four cognitive factors influencing adoption decisions were identified by Dessart et al. (2019): (i) knowledge, (ii) perceived behavioural control, (iii) perceived benefits, and (iv) perceived risk. We are specifically interested in the relationship between knowledge and the adoption of SAP portfolios. Investigating different portfolios allows us to assess whether the relationship between knowledge and the adoption of SAP portfolios is heterogeneous across portfolios. We thus recognise that adopting different combinations of SAPs may require different knowledge sources.

Previous studies revealed a positive relationship between knowledge and the adoption of individual SAPs (Kallas et al., 2010; Läpple and Rensburg, 2011; Pavlis et al., 2016). These studies assessed the role of knowledge in general, without specifying what form of knowledge is related to SAP adoption. Šūmane et al. (2018) argue that a transition towards sustainable agriculture requires different forms of knowledge. Two important forms of knowledge are (i) the current level of knowledge (Ammann et al., 2022) and (ii) the extent to which informal knowledge is acquired (Šūmane et al., 2018).

First, the *level of knowledge* reflects farmers' knowledge about different combinations of SAPs. The level of knowledge depends on information accessibility and the available sources of information (Caffaro et al., 2020). Information provision supports farmers in acquiring more knowledge (Llewellyn, 2007). In line with Läpple and Rensburg (2011), we expect that the level of knowledge is positively correlated with the adoption rate of SAPs. Second, we understand farmers' *informal knowledge* as the knowledge that is acquired through farmers' social networks or social capital (Šūmane et al., 2018). Examples of these informal knowledge practices are attending farmer-to-farmer interactions, participating in study clubs, discussing new practices with crop advisors, and attending demonstration days (Slijper et al., 2022). These forms of informal knowledge have a more experimental character and are closely related to farmers' social norms (Thomas et al., 2020), which often result in improved experience-based knowledge (Šūmane et al., 2018). Therefore, farmers with higher levels of informal knowledge are

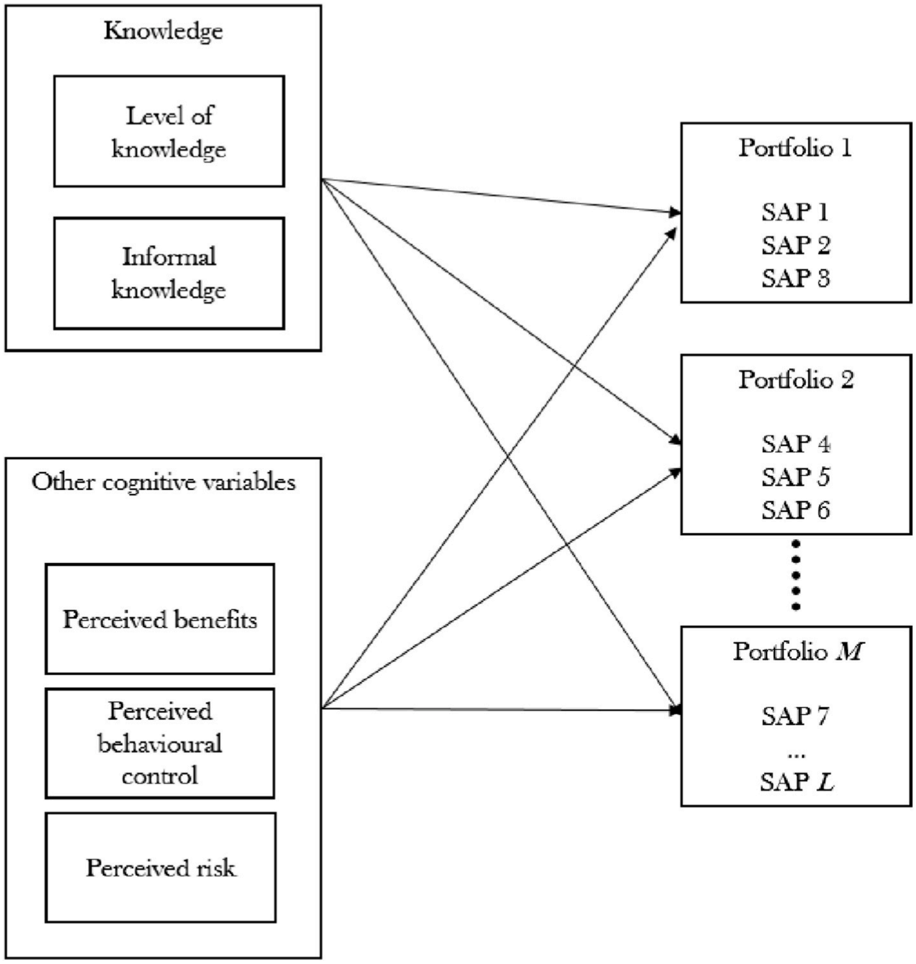

Fig. 1. Conceptual framework depicting the relationship between knowledge and the adoption of SAP portfolios, where *M* is the number of portfolios and *L* is the total number of SAPs.

expected to adopt more SAPs.

We introduce two hypotheses:

H1. The level of knowledge is positively related to the number of SAPs adopted in a portfolio.

H2. Informal knowledge is positively related to the number of SAPs adopted in a portfolio.

We briefly discuss how the three remaining cognitive factors—perceived behavioural control, perceived benefits, and perceived risk—are related to the adoption of SAP portfolios. *Perceived behavioural control* is the perceived ability to overcome obstacles in reaching one's goals (Ajzen, 2002). In the context of SAP portfolios, higher levels of perceived behavioural control imply that farmers see fewer difficulties to adopt different combinations of SAPs. Previous studies found a positive correlation between the level of perceived behavioural control and the adoption rate of several individual SAP, such as organic farming or agri-environmental practices (Kuhfuss et al., 2016). In line with Bopp et al. (2019), we extend this line of reasoning to a SAP portfolio. We expect that higher levels of perceived behavioural control are positively related to the number of SAPs adopted.

Higher *perceived benefits* are expected to result in higher SAP adoption rates. The most important perceived benefits are in the economic or environmental domain (Dessart et al., 2019). The economic domain mostly focuses on the potential of SAPs to increase profitability, reduce costs or receive higher prices. These benefits are positively associated with SAP adoption (Villanueva et al., 2016). In the environmental domain, perceived benefits were associated with higher SAP adoption rates, including improved soil quality (D'Emden et al., 2008), water quality (Yeboah et al., 2015), and lower reliance on pesticides and fertilisers (Dessart et al., 2019).

Sources of risk and uncertainty are inherent to adopting new farming practices. *Perceived risk* reflects a farmer's domain-specific subjective probability of risky events (Hardaker and Lien, 2010). Two key domains are financial and environmental risk perception, which reflect how economic and environmental uncertainty influence adoption decisions. As a higher perceived risk is a barrier to adopting SAPs, perceived risk is negatively associated with SAP adoption (Dessart et al., 2019).

3. Material and methods

3.1. Survey design and data

We conducted an online survey among Dutch arable farmers in June 2021. The survey was distributed by an agricultural market research agency. It took approximately 15 min to complete the survey. We used convenience sampling. One of the limitations of convenience sampling is that agricultural agencies may not have access to all arable farmers. This means that our sample may not be a perfect representation of the population. We are convinced that our sample can be used to address our study aim because of its explorative nature. However, our findings should be interpreted with some caution, as the results cannot be generalised to the general population of Dutch arable farmers.

We sent the survey to about 2,500 Dutch arable farmers, of which 303 respondents completed at least the first part of the survey on farm (er) characteristics. The response rate is approximately 12%. This low response rate may be attributed to the ongoing COVID-19 pandemic at the time that the survey was sent out and that the survey was distributed by email, which made it easy to ignore the invitation to participate. Nevertheless, similar response rates were obtained in other survey-based studies on SAP portfolios (e.g. Weltin et al. (2021) reported a response rate of 13%) or survey-based studies among Dutch farmers (e.g. Slijper et al. (2020) obtained a response rate of 17%). We only included respondents who had completed all relevant sections of the survey in our analysis. This resulted in a sample of 180 respondents .To investigate whether the high non-completion rate of the survey caused potential selection bias, we compare the final sample to the overall population of Dutch arable farmers (see Table A2) and compare farmers who have completed the survey to the ones that have dropped out (see Table A3). Table A2 reveals that our sample is similar to the overall population of Dutch arable farmers for most farm characteristics. The survey sample is marginally larger in terms of land and labour compared to the average Dutch farmer. This is caused by a couple of large farms being present in the sample. However, the labour-to-land ratio is comparable. Table A3 shows that there are no significant differences between the sample of farmers who have completed the survey and the sample that has dropped out for nearly all elicited survey items. All in all, we are confident that our sample is reasonably representative.

To determine if this sample was sufficiently large to run a partial least square structural equation model (PLS-SEM), we followed the inverse square root method proposed by Kock and Hadaya (2018). The inverse square root method is a conservative power analysis, which indicated that a sample size of 180 can detect coefficients between 0.11 and 0.20 at a significance level of less than 5%. This suggests that our sample is sufficiently large to run a PLS-SEM.

The survey consists of three main parts[1]: (i) farm(er) characteristics, (ii) SAP adoption, and (iii) cognitive factors. The first part considers several farm(er) characteristics, such as age, experience, farm household size, agricultural training, gender, education, land, and whether the farmer applied organic practices or not. The second part investigates the combinations of SAPs adopted by farmers in the last five cropping seasons. A full description of the SAPs can be consulted in the Appendix (Table A1). The third part builds on the literature review of Dessart et al. (2019) and investigates the four cognitive factors associated with SAP adoption: (i) knowledge, (ii) perceived benefits, (iii) lack of perceived behavioural control, and (iv) perceived risk. Table 1 presents the full statements and descriptive statistics of these factors.

First, knowledge is measured using three items. The first and second items measure individual knowledge and are based on the statements presented by Läpple and Rensburg (2011) and Kallas et al. (2010). The third item measures farmers' informal knowledge (Läpple and Rensburg, 2011). Second, perceived benefits are measured using four items based on the statements of Vanslembrouck et al. (2002) and Claudy et al. (2014). Third, the (lack of) perceived behavioural control is assessed using two items. Similar statements have previously been used by Claudy et al. (2014). Finally, *perceived risk* is measured by asking farmers how they perceived that several risks affected their farm operations, and in particular their farm's profitability. We anchor risk perceptions to profitability, as Spiegel et al. (2020) showed that European farmers perceived economic risks as most severe. For both perceived benefits and risks, we focus on the environmental dimension as SAP portfolios have environmental benefits that potentially reduce these perceived risks.

[1] The survey included an introduction section containing information about the study. The respondents were asked to sign a consent form and could only continue the survey if they signed this form. The consent form ensures that the ethical aspects of this study are handled well. It has been approved by the Social Sciences Ethics Committee of Wageningen University. Twelve respondents tested the survey after which some questions were omitted or rephrased.

Table 1
Item wordings and summary statistics (N = 180).

Name	Item	Mean	St dev
SAP	Number of adopted SAPs (ranging from 0 to 14 adopted SAPs)	6.41	3.16
Knowledge			
Level of knowledge			
	To what extent do you agree or disagree with the following statements? 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree)[a].		
$Know_1$	I lack adequate knowledge about the benefits of using multiple SAPs simultaneously	3.39	1.49
$Know_2$	I lack knowledge on how to adopt the best combinations of SAPs	3.43	1.48
Informal knowledge			
$Know_3$	How often did you discuss SAPs with other (neighbouring) farmers, agricultural experts or extension agents in the last cropping season? 4-point scale: 1 = never; 2 = rarely; 3 = a few times; 4 = regularly.	3.09	0.93
Risk perception			
	When thinking of your farm operations and profitability, how concerned are you regarding the following issues? 5-point scale ranging from 1 (not worried at all) to 5 (extremely worried).		
RP_1	Your farm's soil quality	2.79	1.07
RP_2	The impacts of chemical inputs used in crop farming on the environment	2.57	1.17
RP_3	The impacts of chemical residues in food products on consumers' health	2.20	1.10
Perceived benefits			
	If you have adopted different combinations of SAPs, what are your reasons for doing so? 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree)		
PB_1	Increase crop resistance to pests and diseases	5.42	1.52
PB_2	Increase crop resistance to extreme weather and extreme climate conditions	5.54	1.53
PB_3	Decrease the amount of pesticides used on my farm	4.88	1.72
PB_4	Improve biodiversity	4.73	1.70
Lack of perceived behavioural control			
	To what extent do the following factors limit your adoption of different (combinations of) SAPs? 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree).		
PBC_1	I foresee several difficulties when implementing multiple SAPs simultaneously	4.31	1.61
PBC_2	I am not convinced about the effectiveness and efficacy of using multiple SAPs together	4.69	1.54

[a] Reversed scores are presented for farmers' level of knowledge to ensure that these statements follow the same direction as informal knowledge.

3.2. Methodology – a three-stage approach

We adapt the three-stage approach proposed by Weltin et al. (2021) to the context of Dutch agriculture. The first stage constructs the SAP portfolios. The second stage assesses interdependencies across SAP portfolios. Finally, the third stage explores the relationship between knowledge and the adoption of SAP portfolios.

3.2.1. Stage 1: Constructing SAP portfolios

We employ correlation explanation (CorEx) (Ver Steeg and Galstyan, 2014) to construct SAP portfolios. Each SAP is a dummy variable that turns 1 if a SAP has been adopted by a farmer in the past five cropping seasons and 0 otherwise. Hence, our dataset is dichotomous and high-dimensional. CorEx is a suitable method to reduce dimensionality in dichotomous datasets[2] (Ver Steeg and Galstyan, 2014). It applies information theory to run an unsupervised machine learning algorithm, which identifies latent factors (M)—in our case SAP portfolios—consisting of individual SAPs (L) (Fig. 1).

CorEx builds on the concept of total correlation (TC), which is the multivariate mutual information among a set of SAPs. The SAPs that share most mutual information are clustered into portfolios, meaning that a portfolio exists of SAPs that are often jointly adopted or are not adopted. Following Ver Steeg and Galstyan (2014), the mutual information is the information shared across two SAPs:

$$I(L_i;L_a) = H(L_i) + H(L_a) - H(L_i, L_a) \tag{1}$$

where i and a refer to different SAPs and $H(L_i) = -\log p(L_i)$ is the entropy.

TC generalises mutual information (Li et al., 2022). It does this by allowing n-wise combinations of SAPs while mutual information is restricted to pairwise comparison. TC is defined as:

$$TC\ (L_1, \ldots, L_n) = \sum_{i=1}^{n} H(L_i) - H(L_1, \ldots, L_n) = D_{KL}\left(p(L_1, \ldots, L_n) \middle\| \prod_{i=1}^{n} p(L_i)\right) \tag{2}$$

where $L_1, \ldots, L_n$ refers to SAP 1, …, n. D_{KL} is Kullback-Leibler divergence of the joint probability density and the product of the marginal densities. Fully independent SAPs obtain a TC of zero while higher dependences across SAPs increases TC. The conditional total correlation can be obtained by conditioning SAPs L on portfolios K. It builds on the Kullback-Leibler divergence of two conditional probability distributions (Li et al., 2022) and reads as:

$$TC(L|K) = \sum_{i} H(L_i|K) - H(L|K) = D_{KL}\left(p(l|k) \middle\| \prod_{i=1}^{n} p(l_i|k)\right) \tag{3}$$

where l and k are the conditional probability distributions of L and K.

High-dimension datasets lack a straightforward application of TC (Ver Steeg and Galstyan, 2014). To overcome this issue, CorEx adopts a latent factor modelling approach that constructs several SAP portfolios (K). K captures the dependencies across individual SAPs L_i. We measure the proportion that K explains correlations among L by computing the decrease in TC:

$$TC(L) - TC(L|K) = \sum_{i=1}^{n} I(L_i;K) - I(L;K) \tag{4}$$

The optimal factor model is obtained by reconstructing m latent SAP portfolios K_j ($j = 1, \ldots, m$). The function that optimises the lower bound of equation (4) reads as:

$$TC(L) \geq \max_{p(K_j|L)} \sum_{i=1}^{n} I(L_i;K) - I(L;K) = \sum_{j=1}^{m}\left(\sum_{i=1}^{n} \alpha_{i,j} I(L_i;K_j) - (K_j;L)\right) \tag{5}$$

where $\alpha_{i,j}$ is a free parameter, which optimal value is obtained by iterating t times. Initialising at $t = 0$ and updating $\alpha_{i,j}$ is done using:

$$\alpha_{i,j}^{t+1} = (1-\lambda)\alpha_{i,j}^{t} + \lambda\alpha_{i,j}^{**} \tag{6}$$

where $\alpha_{i,j}^{**} = \exp\left(\gamma\left(I(L_i,K_j) - \max_{j}\left(I(L_i,K_j)\right)\right)\right)$ with λ and γ as constants. We set t to 1,000 iterations and repeat the algorithm 100 times, which results in a stable maximisation of TC while limiting computation time. The optimal number of portfolios is obtained by running CorEx for different numbers of portfolios (for m ranging from 2 to 6 portfolios), after which the number of portfolios that maximises TC is selected. We use the R library *rcorex* (Rooney, 2021) to run CorEx.

3.2.2. Stage 2: Assessing interdependencies across SAP portfolios

We explore the interdependence of SAP portfolios using a multivariate probit (MVP) model (Wooldridge, 2010). MVP simultaneously estimates a system of univariate probit equations—i.e. a single equation for each of the portfolios—and allows the error terms of these equations to be correlated. This correlation may arise if similar farm(er) characteristics are associated with the adoption of multiple SAP across different portfolios (Kassie et al., 2015). The existence of positive (negative) correlations among error terms indicates complementarity (substitutability) across SAP portfolios.

We define the M-equation MVP as:

$$y_{im}^{*} = \beta_{m}^{'} X_{im} + \varepsilon_{im} \quad m = 1, \ldots, M \tag{7a}$$

$$y_{im} = 1 \text{ if } y_{im}^{*} > 0 \text{ and 0 otherwise} \tag{7b}$$

where y_{im} is a dichotomous variable that turns 1 if farmer i adopts at least one SAP within portfolio m and 0 otherwise, X_m is a vector of explanatory farm(er) characteristics, and ε_{im} are the error terms of the equations. ε_{im} is multivariate normally distributed with a zero conditional mean and a normalised variance to unity—i.e. $MVN \sim (0,\Omega)$. The symmetric variance-covariance matrix Ω reads as:

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \cdots & \cdots & \cdots & \rho_{1M} \\ \rho_{21} & 1 & & & & \vdots \\ \vdots & & 1 & & & \vdots \\ \vdots & & & 1 & & \vdots \\ \vdots & & & & 1 & \rho_{M-1M} \\ \rho_{M1} & \cdots & \cdots & \cdots & \rho_{MM-1} & 1 \end{bmatrix} \tag{8}$$

where ρ represents the pairwise correlation coefficients of the error terms of two equations. We use a likelihood ratio test to determine whether the correlations between the error terms are jointly equal to zero or not. Estimating separate univariate probit models is inefficient if the decisions to adopt SAP portfolios are interrelated. In these cases, multivariate models are the preferred specifications[3]. MVP is estimated using simulated maximum likelihood. 100 draws are taken from the Geweke-Hajivassiliou–Keane simulator. This number of draws results in stable pairwise correlation coefficients: a further increase in the number of draws hardly changes the pairwise correlation coefficients (see Appendix, Figure A1). We use the Stata command *mvprobit* (Cappellari and Jenkins, 2003) to estimate the MVP.

The explanatory farm(er) characteristics included in the MVP are the level of knowledge about SAP, informal knowledge, farmer experience, farm household size, diversification, and farmers' expectations about

[2] We also considered alternative methods to reduce dimensionality, such as principal component analysis (PCA) or multiple correspondence analysis (MCA). However, PCA is less suitable to reduce dimensionality of dichotomous variables as it is designed for continuous variables. MCA could be an alternative method to reduce dimensionality of dichotomous dataset but performs less well for high dimensional data.

[3] To investigate the robustness of our findings to alternative model specifications and if our finite sample may bias our findings, we also investigate (i) univariate probit models, (ii) bivariate probit models, and (iii) multivariate ordered probit models. The univariate probit models estimate a separate equation for each SAP portfolio. The bivariate probit models investigate the correlations between two selected SAP portfolios. The multivariate ordered probit model categorises the number of SAP within a portfolio into multiple categories and investigates if these portfolios act as complementary or substitutes. We use the Stata commands probit, mvprobit (Cappellari and Jenkins, 2003), and cmp (Roodman, 2007) to estimate these models.

the effect of SAPs on farm profitability[4]. These selected farm(er) characteristics are identified by previous studies as important drivers of SAP adoption (Knowler and Bradshaw, 2007; Prokopy et al., 2008) and have been included in earlier adoption decision models (e.g. Bopp et al., 2019; Weltin et al., 2021). We excluded land as a control variable as it was often missing. Including land in the main model would reduce our sample size to 120 farmers. As a robustness check, we estimate the MVP model including land. The descriptive statistics of the farm(er) characteristics are available in the Appendix (Table A2).

3.2.3. Stage 3: Exploring the relationship between knowledge and SAP adoption

We run a partial least squares structural equation model (PLS-SEM) to explore how knowledge is related to the adoption of SAP portfolios. We treat the number of SAPs adopted within a portfolio as a continuous variable. Most of the measured constructs in our survey are latent, implying that they cannot be directly measured. PLS-SEM is a non-parametric multivariate technique that is suitable to estimate relationships between latent constructs by combining a structural and measurement model (Hair et al., 2016).

The structural model investigates relationships among latent constructs. It describes how knowledge, risk perception, perceived behavioural control, and perceived benefits are correlated with the adoption of SAP portfolios. The measurement model explains how each latent construct is measured in a formative or reflective way. On the one hand, formative measurement models suggest the existence of a relationship pointing from specific items to latent constructs, when changing items cause the construct to change (Diamantopoulos and Siguaw, 2006). On the other hand, reflective measurement models investigate relationships from a latent construct to the items, when changing a latent construct causes changes in the items (Diamantopoulos and Siguaw, 2006).

PLS-SEM is a suitable estimation approach for our study as we combine formative (risk perception and perceived benefits) and reflective measurement models (knowledge and perceived behavioural control) into a structural model. Traditional covariance-based SEMs struggle to combine formative and reflective measurement models. We use the R library *SEMinR* (Ray et al., 2021) to estimate the PLS-SEM.

4. Results and discussion

4.1. Stage 1: Correlation explanation (CorEx)

The optimal number of SAP portfolios is three (Table 2), as this number of portfolios maximises the total correlation explained[5]. These SAP portfolios are presented in Table 3. These portfolios consist of combinations of SAPs adopted by Dutch arable farmers and do not necessarily reflect the optimal SAP portfolios from an agronomic perspective. It shows that portfolio 1 consists of five SAPs: integrated pest management, land reforming, manure management, precision farming, and water management. This is a diversified portfolio that includes SAPs aimed at improving land or water management. Portfolio 1 distinguishes itself from the other portfolios as these SAPs require investments in technology, such as storage systems for manure management, investments in precision farming machinery or optimized irrigation systems to improve water management. Portfolio 2 contains greening measures specified by the CAP—i.e. cover crops, legumes (intercropping and rotation)—and genetically improved seeds. In the Netherlands, these greening measures are used as cross-compliance to obtain decoupled direct payments. Hence, the adoption of most of these SAPs is stimulated by agricultural policymakers. Portfolio 3 consists of SAPs that reduce chemical fertiliser and pesticide usage, composting, microbial applications, mulching, and tillage measures. This portfolio represents a specialised combination of SAPs, which are aimed at improving soil health and quality and reducing farmers' reliance on chemical fertilisers and pesticides.

Table 2
Total correlation explained for different numbers of SAP portfolios.

Number of portfolios	Total correlation explained
2	0.658
3	0.676
4	0.607
5	0.585
6	0.550

Table 3
The SAP portfolios identified by CorEx. Standard deviations are presented in parentheses.

Portfolio	SAP	Mean[a]
Portfolio 1 (investments in technology)		2.239 (1.562)
	Integrated pest management	0.744
	Land reforming	0.228
	Manure management	0.367
	Precision farming	0.506
	Water management	0.394
Portfolio 2 (cross-compliance of the CAP and genetically improved seeds)		1.483 (1.217)
	Cover crops	0.628
	Genetically improved seeds	0.278
	Legumes intercropping	0.222
	Legumes rotation	0.356
Portfolio 3 (soil health improvement and pesticide and fertiliser reduction)		2.689 (1.420)
	Reduction of chemical fertiliser and pesticides	0.783
	Composting	0.356
	Microbial applications	0.378
	Mulching	0.522
	Reduced or no tillage	0.650

Notes.
[a] Mean of portfolio 1, 2, or 3 refers to the average number of SAPs adopted within a portfolio. Note that portfolio 2 contains four SAPs while portfolios 1 and 3 contain five SAPs. No standard deviations are presented for individual SAPs as these variables are measured dichotomously.

4.2. Stage 2: Multivariate probit model

Table 4 presents the correlation coefficients of the error terms for different probit specifications[6]. It reveals complementary relationships between each of the three portfolios, as there are significant positive correlation coefficients for all model specifications. These findings are in line with Weltin et al. (2021) and Kassie et al. (2015), who mostly found positive correlations between the adoption of different SAP portfolios. This means that SAPs from different portfolios are often jointly adopted. Hence, farmers are spreading risks by diversifying across different SAP portfolios.

[4] We omitted organic farming as an explanatory variable as it was one of the SAPs included in the questionnaire.

[5] This optimal number of portfolios only includes SAPs that are adopted by at least 20% of the farmers. As a robustness check, we investigated the number of SAP portfolios to an adoption threshold of 10% or to a scenario that includes all SAPs. Table A3 shows that the optimal number of SAP portfolios remains three.

[6] The average partial effects of the explanatory variables are omitted for the sake of brevity. These can be found, as well as the robustness check for models including land, in the Appendix (Table A4). In general, it shows that the average partial effects are stable—in terms of magnitude, sign, and significance—across the different models. This increases our confidence in the presented findings.

Table 4
Correlation coefficients of the error terms (ρ) for different portfolio equations under various model specifications.

	Multivariate probit	Ordered multivariate probit	Bivariate probit: portfolio 1, 2	Bivariate probit: portfolio 1, 3	Bivariate probit: portfolio 2, 3
ρ_{12}	0.270*	0.232**	0.250*		
	(0.142)	(0.091)	(0.148)		
ρ_{13}	0.743***	0.403***		0.751***	
	(0.120)	(0.064)		(0.118)	
ρ_{23}	0.567***	0.315***			0.576***
	(0.145)	(0.080)			(0.158)
Farm(er) characteristics[a]	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−191.574	−829.330	−165.981	−97.397	−130.340
Wald test (χ^2)	58.27***	81.16***	44.26***	37.17***	31.67***
Wald test (df)	18	18	12	12	12
N	180	180	180	180	180

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Likelihood ratio test of the multivariate probit model: $\chi^2(3) = 22.524$, p-value = 0.000.
[a] Average partial effects of the farm(er) characteristics and other control variables are omitted for the sake of brevity. “Yes” implies these variables are included in the model.

4.3. Stage 3: Partial least square structural equation model (PLS-SEM)

We estimate four PLS-SEM: a general model investigating the total number of SAPs adopted and three separate models representing each of the SAP portfolios. Before discussing the structural model, we first assess the reflective and formative measurement models.

Assessing the reflective measurement model requires an understanding of internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2016). The evaluation of the initial models shows a lack of internal consistency reliability as the items representing perceived behavioural control obtained a Cronbach’s alpha smaller than 0.7. Hence, we drop one item that measures perceived behavioural control. In the final model, only PBC_1 is included. Tables A7-A8 show that for the level of knowledge, satisfactory levels of Cronbach’s alpha (larger than 0.7), composite reliability (larger than 0.7), and average variance explained (larger than 0.5) are obtained. Finally, we assess discriminant validity using the heterotrait-monotrait (HTMT) ratio. The HTMT ratios are significantly lower than 1, indicating that discriminant validity is obtained (Table A9-A12).

The formative measurement model assessment validates the convergent validity, absence of multicollinearity, and significance of outer weights and loadings (Hair et al., 2016). We conduct a redundancy analysis to assess convergent validity for the two formative constructs in our model—i.e. perceived risk and perceived benefits. One or two reflective measures of each construct were collected and correlated to the corresponding formative items. Table A13 shows that convergent validity is obtained as all R^2 exceed 0.5. All variance inflation factors (VIF) are below 3 (Table A14 and Table A15), indicating that multicollinearity is not present at critical levels. Finally, the significance of the outer weights and loadings are assessed. Table A14 shows that either the outer weights or loadings are significantly different from zero for all items. Hence, we conclude that the reflective and formative measurement models are of sufficient quality and proceed to the structural model assessment.

The presented path coefficients (Table 5) are obtained using the percentile method for bootstrapping. The order of the f^2 effect sizes follows the same rank as the bootstrapped parameter estimates (Table A16), suggesting that satisfactory effect sizes are obtained and are consistent with the parameter estimates.

The level of knowledge and informal knowledge are significantly associated with SAP adoption in the general model and the models investigating portfolios 1 and 3. For these models, hypotheses 1 and 2 are confirmed. The positive relationship between the level of knowledge and SAP adoption implies that informing farmers about combinations of SAPs could be an effective direction towards increasing farmer knowledge. These findings are in line with previous studies that focused on a single SAP. For instance, D’Emden et al. (2008) found that no-till decisions were positively related to adoption decisions. The positive

Table 5
Path coefficients of the PLS-SEM. Bootstrapped 95% confidence intervals are presented in squared brackets.

	General model[a]		Portfolio 1		Portfolio 2		Portfolio 3	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.199**	[0.009; 0.389]	0.160**	[0.036; 0.354]	0.100	[-0.070; 0.280]	0.201**	[0.015; 0.393]
Informal knowledge	0.319***	[0.190; 0.438]	0.357***	[0.228; 0.476]	0.095	[-0.040; 0.223]	0.237***	[0.099; 0.367]
Lack of PBC	−0.019	[-0.218; 0.171]	−0.097	[-0.294; 0.089]	−0.052	[-0.237; 0.125]	0.107	[-0.082; 0.303]
Risk perception	−0.123*	[-0.248; 0.015]	−0.109*	[-0.234; 0.017]	−0.077	[-0.231; 0.118]	−0.112	[-0.246; 0.045]
Benefits	0.209**	[0.040; 0.358]	0.042	[-0.103; 0.172]	0.219*	[-0.050; 0.366]	0.307***	[0.166; 0.438]
AIC	−38.265		−36.961		−1.565		−30.842	
BIC	−19.108		−17.804		17.593		−11.684	
R^2	0.242		0.236		0.067		0.211	
Adjusted R^2	0.220		0.214		0.040		0.188	

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. The following PLS-SEM settings were used: maximum number of iterations is set to 300 with a stop criterion of 10^{-7} and 10,000 bootstrap repetitions using the path weighting method. The confidence intervals are based on the bootstrapped mean and standard errors. For some path coefficients, the confidence intervals are slightly asymmetric as a result of applying a non-parametric method.
[a] The general model considers all SAPs in a single portfolio.

relationship between informal knowledge and SAP adoption suggests that discussing SAPs with others is a successful strategy to increase SAP adoption rates in the general model or the models investigating portfolios 1 and 3. Our findings are backed up by Šūmane et al. (2018) who underline the importance of informal knowledge in enhancing farm sustainability. Furthermore, D'Emden et al. (2008) found that farmers who discuss no-till decisions with others are more likely to adopt no-till practices than those who donot. Finally, the importance of knowledge sharing has also been highlighted by Lamkowsky et al. (2021) in the context of economic productivity and nitrogen pollution in Dutch dairy farms, as it may help close the large existing gap between best-practice farmers and others.

Overall, our findings reveal that the path coefficients of the general model and the models investigating portfolios 1 and 3 are fairly similar in terms of signs and significance. However, both types of knowledge are not significantly related to the adoption of SAPs in portfolio 2. A possible explanation for this could be that the adoption of several SAPs in portfolio 2 is stimulated by the CAP. For instance, cover crops and legumes are part of the cross-compliance to receive decoupled direct payments. Hence, only perceived benefits are significantly correlated to the adoption of SAP in portfolio 2. These heterogeneous effects suggest would not have been unravelled if only the general model had been estimated. This reveals an advantage of analysing multiple SAP portfolios: it helps to design effective policy interventions that could persuade farmers to adopt certain combinations of SAPs. For instance, a combination of knowledge transfer (portfolio 1 and 3) and decoupled direct payments (portfolio 2) could persuade farmers to adopt a wide range of SAPs.

We find that a lack of perceived behavioural control is not related to farmers' adoption decisions. This consistently holds for all portfolios, suggesting that difficulties to adopt combinations of SAPs are not perceived as a barrier. A possible explanation for this surprising finding could be that farmers are convinced that adopting SAPs is relatively easy and, therefore, not hampered by a lack of perceived behavioural control. These findings contradict previous studies describing that perceived behavioural control influences farmers' intention to adopt or their actual adoption decisions (Bopp et al., 2019).

Risk perception is negatively associated with SAP adoption in the general model and the model investigating portfolio 1 but unrelated to adoption in portfolios 2 and 3. This implies that farmers with higher environmental risk perceptions adopt fewer SAPs, suggesting that high levels of perceived risk act as a barrier to adopting SAPs. These findings contradict previous studies suggesting that higher environmental risk perceptions are positively associated with the adoption of sustainable practices to mitigate these risks (Arbuckle et al., 2015; Toma and Mathijs, 2007). A possible explanation for these contradictory findings could be that we anchor our environmental risk perception to farmers' profitability—i.e. we asked farmers to indicate how concerned they are about the effect of environmental risks on the profitability of their farm—suggesting an indirect relationship to financial risk perception. As previous studies found that financial risk perceptions are negatively related to the adoption of SAPs (Trujillo-Barrera et al., 2016), this could explain the negative association between environmental risk perception and SAP adoption.

Perceived benefits are positively correlated to SAP adoption in the general model and the models investigating portfolios 2 and 3. These findings are confirmed by studies that describe how higher perceived benefits lead to higher SAP adoption rates (Villanueva et al., 2016; Yeboah et al., 2015). A possible explanation for the non-significant relationship between the perceived benefits and SAP adoption in portfolio 1 could be that these SAPs require initial investments in technologies. For these SAPs, access to finance may be a more important factor to explain adoption.

Additionally, we run a series of robustness checks that consider different combinations of control variables and a model that includes an interaction effect between the level of knowledge and informal knowledge. Fig. 2 presents the 90% confidence intervals[7] for alternative model specifications. In general, our findings are consistent across alternative model specifications as none of the 90% confidence intervals of the level of knowledge and informal knowledge contains 0 for the general model (Fig. 2A), portfolio 1 (Fig. 2B), and portfolio 3 (Fig. 2D). This means that the level of knowledge and informal knowledge are positively correlated to SAP adoption in these models. Fig. 2C depicts that individual knowledge is not significantly correlated to adopting more SAPs in portfolio 2 across all model specifications. However, our results are not fully robust to alternative model specifications when inspecting the role of informal knowledge. Informal knowledge is only associated with SAP adoption in portfolio 2 if perceived benefits are omitted from the model (i.e. model specifications 2, 3, 4, and 6). This indicates that the association between informal knowledge and SAP adoption in portfolio 2 is hampered by perceived benefits.

4.4. Limitations

We discuss two limitations of this study. First, the use of convenience sampling methods combined with a high non-completion rate of the survey may imply that our sample cannot be fully classified as a random sample. Caution is required when interpreting our results, as the techniques employed focus on internal validity rather than external validity. The generalisation of our findings to other settings may be compromised. Second, the measurement models of perceived behavioural control and informal knowledge are only based on a single item. This may have decreased the validity of these constructs and disallowed assessing the reliability of these constructs. We intended to measure perceived behavioural control on a multi-item scale. However, lacking reliable internal consistency, one item had to be removed. Using multi-item scales could have improved the measurement of perceived behavioural control and informal knowledge.

5. Conclusions

This study investigated the relationship between farmers' knowledge and the adoption of different SAPs. Using survey data from 180 Dutch arable farmers, we investigated the combinations of SAPs that were jointly adopted into portfolios. Three SAP portfolios were identified. The first portfolio contained technology-driven SAPs that require an initial investment. The second portfolio mostly contained greening measures that are part of the CAP's cross-compliance. The third portfolio was aimed at improving soil health and quality and reducing farmers' reliance on chemical fertilisers and pesticides. Furthermore, we found a complementary relationship among the three SAP portfolios. This implies that adopting more SAPs within a portfolio was correlated with adopting more SAPs in other portfolios. Finally, our results revealed that the level of knowledge and informal knowledge are heterogeneously associated with different SAP portfolios. Farmers with more knowledge about combinations of SAPs and farmers who acquired more informal knowledge adopted more technologically driven SAPs (portfolio 1) and SAPs aimed at improving soil health and reducing fertiliser and pesticide usage (portfolio 3). However, knowledge was not related to the adoption of cover crops and other greening measures (portfolio 2).

This study has important implications for agricultural policymakers who aim at enhancing the sustainability and resilience of arable farmers. Policymakers should foster farm sustainability by increasing the adoption rates of SAPs, which could be stimulated by improving knowledge about SAPs and sharing knowledge in a social setting. Focusing on sharing knowledge through social capital could help policymakers to

[7] We present 90% confidence intervals because we consider significant associations in Table 4 at a level of $\alpha = 0.10$. To consistently discuss our results, we present 90% confidence intervals. The full model output of these robustness checks can be found in the Appendix (Table A.16-A.19).

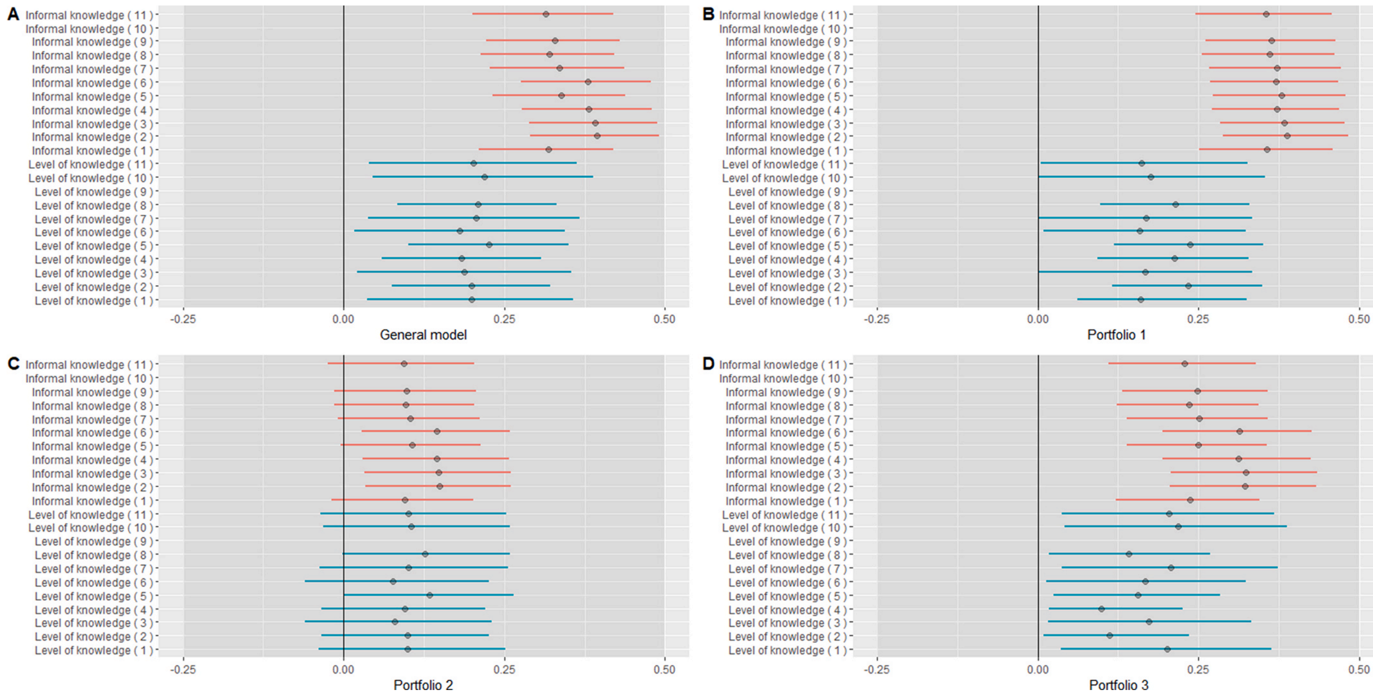

Fig. 2. Coefficient plots of the bootstrapped 90% confidence intervals for informal knowledge and the level of knowledge under different model specifications. Numbers in parentheses refer to different model specifications. The following constructs are included in these models: 1: original model, 2: informal knowledge (*inf know*) and level of knowledge (*lev know*), 3: inf know, lev know, and lack of perceived behavioural control (*PBC*), 4: inf know, lev know, and risk perception (*RP*), 5: inf know, lev know, and perceived benefits (*PB*), 6: inf know, lev know, PBC, and RP, 7: inf know, lev know, PBC, and PB, 8: inf know, lev know, RP, and PB, 9: inf know, PBC, RP, and PB (lev know excluded), 10: lev know, PBC, RP, and PB (inf know excluded), 11: original model including an interaction term between inf know and lev know.

stimulate farm resilience, especially in terms of transformations toward sustainable production systems. In line with CAP 2023–2027 reform, we recommend policymakers specifically target farm advisory services to foster informal knowledge sharing within the Agricultural Knowledge and Innovation Systems (AKIS 2.0). It is recommended to share knowledge informally during farm demonstration days, study clubs or other extension services. Besides effective knowledge transfer, subsidies may also persuade farmers to adopt SAP. Some SAPs are already stimulated by the CAP's cross-compliance to receive decoupled direct payments (e.g. cover crops and legumes). Maximising the economic, environmental, and social benefits of SAP portfolios, requires a combination of economic and behavioural policy instruments. This may be achieved through the combined effect of payments for ecosystem services, which facilitates informal knowledge sharing to increase SAP adoption rates.

We have three recommendations for further research. First, researchers could investigate the non-adoption of SAP and its related barriers to adoption. Second, neighbourhood effects in the diffusion of innovation and knowledge sharing could be studied in the context of SAP portfolios. Third, the effectiveness of combined economic and social policy interventions to persuade farmers to adopt SAPs could be further investigated.

CRediT authorship contribution statement

Thomas Slijper: Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Visualization. **Annika F. Tensi:** Writing – review & editing, Supervision, Project administration. **Frederic Ang:** Writing – review & editing, Supervision, Project administration. **Beshir M. Ali:** Conceptualization, Writing – review & editing, Supervision, Project administration. **H.J. van der Fels-Klerx:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Thomas Slijper reports financial support was provided by EU Horizon 2020. Annika F. Tensi reports financial support was provided by EU Horizon 2020. Frederic Ang reports financial support was provided by EU Horizon 2020. Beshir M. Ali reports financial support was provided by EU Horizon 2020. H.J. van der Fels-Klerx reports financial support was provided by EU Horizon 2020.

Data availability

Data are available upon request.

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Appendix

Table A1
Full description of the sustainable agricultural practices (SAPs) considered in this study

SAP	Full description SAP
Portfolio 1	
Integrated pest management	Pest management that combines biological, chemical, physical, and cultural practices.
Land reforming	Reducing surface runoff of water and topsoil through forming terrace, and other slope reducing and stabilizing technologies (e.g. soil and stone bunds).
Manure	Improved manure application practices. Using improved treatment techniques (e.g. solid and urine separation), storage systems and application techniques.
Precision farming	Farm management strategy based on measurement, observation, and response to address inter- and intra-field variability through the use of technologies such as variable rate nutrient application and variable rate irrigation systems to apply the optimum amount of chemicals/manure and water in the farm, respectively.
Water management	Adoption of an optimized irrigation management, also by implementing infrastructures/facilities, in order to minimize irrigation water losses.
Portfolio 2	
Cover crops	Cover crops and green manuring. The use of legumes (e.g. clover), and non-legumes (e.g. rye) by incorporating into the soil as green manures to improve soil fertility and reduce erosion.
Genetically improved seeds	Use of genetically improved wheat or potato varieties such as drought, pest or salt-tolerant varieties.
Legumes intercropping	Intercropping with legumes and/or polyculture farming. Different and less competitive crops grown together with wheat/potato to optimize biomass yield and improve soil fertility and environmental quality.
Legumes rotation	System of rotating legume and non-legume crops in the same field to maintain soil fertility.
Portfolio 3	
Chemical reduction	Reduction of the use of chemical fertilizers and pesticides.
Composting	Recycling technique converting waste into nutrient-rich humus with high soil organic matter using microbes.
Microbial applications	Soil addition containing beneficial microorganism-based products such as plant growth promoting rhizobacteria (PGPR) to improve soil health and enhance crop resistance to biotic and abiotic stress.
Mulching	Shallow layer of crop residues/straws or grass at the soil/air interface to improve soil quality, improved water retention, and reduce soil erosion.
Reduced or no tillage	Practices of zero tillage or tillage that minimizes the number of tillage passes, where soil aggregate disruption is reduced for reducing soil erosion.
Excluded by thresholds (i.e. SAPs that are adopted by less than 20% of the farmers in our sample)	
Contour farming	The practice of tilling or planting sloped land along lines of consistent elevation in order to conserve rainwater and to reduce soil erosion.
Agroforestry	Integrating trees and shrubs into croplands and/or grassland for forming multifunctional farming systems providing multiple benefits by optimized utilization of resources (e.g. nutrients, light, and water).
Fallow management	Using the fallow period for conserving and storing rainfall water into the soil and for reducing soil erosion.
Organic farming	Certified organic farming
Biochar	Soil application of carbon (char) produced by high temperature pyrolysis from organic feedstock biomass, mainly animal manure, food and green wastes, and woody residues.

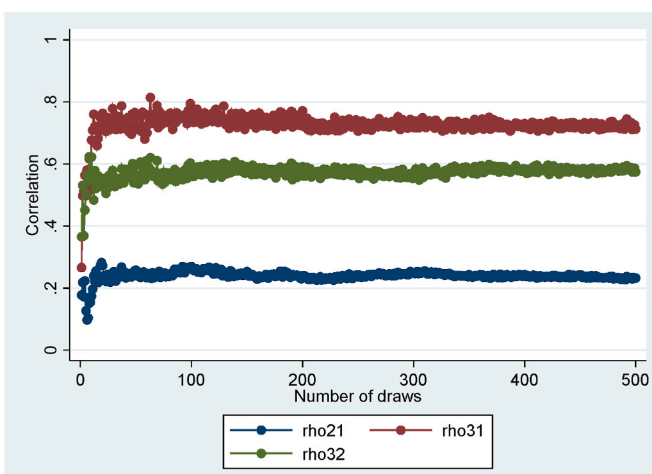

Fig. A1. Pairwise correlation coefficients of the error terms of different multivariate probit equations for different number of draws

Table A2
Descriptive statistics comparing the final sample to the overall population of Dutch arable farmers (based on national statistics)

Variable	Sample			National Statistics	
	N	Mean	St dev	Mean	Source
Age (year)	167	52.36	10.07	54.86	CBS (2022)
Main crop	180				CBS (2022)
Potato		62%		60.04%	
Wheat (incl. other types)		38%		39.96%	

(continued on next page)

Table A2 (*continued*)

Variable	Sample			National Statistics	
	N	Mean	St dev	Mean	Source
Organic (%)	180	2.78%		2.81%	CBS (2022)
Total cropland (ha)	120	73.50	74.25	63.36	Agrimatie (2022)
Total labour (FTE)	103	2.04	3.68	1.55	Agrimatie (2022)
Labour/land (FTE/ha)	103	0.03		0.03	Agrimatie (2022)

Table A 3
Descriptive statistics comparing the final sample to the sample that dropped out of the survey.

	Dropped out			Sample		
	N	Mean	St dev	N	Mean	St dev
Farm(er) characteristics						
Experience (years)	114	31.34	13.51	180	28.61*	11.78
Age (years)	102	53.86	11.30	167	52.36	10.07
Farm household size (persons)	107	3.63	1.58	180	3.77	2.13
Shannon Diversity Index	123	1.18	0.45	180	1.25	0.44
Sustainable agricultural practices (SAPs)						
Total number of SAPs adopted	57	5.75	4.05	180	6.41	3.60
Number of SAPs in portfolio 1	57	2.11	1.35	180	2.24	1.57
Number of SAPs in portfolio 2	57	1.21	1.16	180	1.48	1.23
Number of SAPs in portfolio 3	57	2.43	1.44	180	2.69	1.44
Knowledge						
$Know_1$	48	3.76	1.69	180	3.39	1.49
$Know_2$	48	3.71	1.80	180	3.43	1.48
$Know_3$	116	2.84	0.99	180	3.09*	0.93
Risk perception						
RP_1	115	2.65	1.16	180	2.79	1.07
RP_2	115	2.57	1.28	180	2.57	1.17
RP_3	115	2.09	1.06	180	2.20	1.10
Perceived benefits						
PB_1	53	5.55	1.64	180	5.42	1.52
PB_2	53	5.39	1.66	180	5.54	1.53
PB_3	53	4.79	1.89	180	4.88	1.72
PB_4	53	4.72	1.76	180	4.73	1.70
Lack of perceived behavioural control						
PBC_1	48	4.19	1.94	180	4.31	1.61
PBC_2	48	4.41	1.98	180	4.69	1.54

Notes: The asterisks refer to p-values of a *t*-test, comparing the means of both groups. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A4
Total correlation explained by CorEx under different adoption thresholds and different number of SAP portfolios

Scenario	Number of portfolios	Total correlation explained
20% adoption threshold	2	0.658
	3	**0.676**
	4	0.607
	5	0.585
	6	0.550
10% adoption threshold	2	0.802
	3	**0.819**
	4	0.810
	5	0.772
	6	0.713
No adoption threshold	2	0.904
	3	**0.952**
	4	0.942
	5	0.916
	6	0.902

Table A5
Average partial effects of different probit specifications with robust Newey-West standard errors in parentheses.

	Multivariate probit	Ordered multivariate probit[a]	Bivariate probit; portfolio 1 and 2	Bivariate probit; portfolio 1 and 3	Bivariate probit; portfolio 2 and 3	Univariate probit, portfolio 1	Univariate probit, portfolio 2	Univariate probit, portfolio 3
Portfolio 1								
Level of knowledge	0.052***	0.200***	0.049***	0.051***		0.048***		
	(0.016)	(0.058)	(0.016)	(0.016)		(0.016)		
Informal knowledge	0.091***	0.501***	0.090***	0.093***		0.091***		
	(0.023)	(0.089)	(0.024)	(0.023)		(0.024)		
Experience	−0.002	−0.006	−0.002	−0.002		−0.002		
	(0.002)	(0.007)	(0.002)	(0.002)		(0.002)		
Farm household	0.005	0.067	0.006	0.004		0.004		
	(0.016)	(0.041)	(0.016)	(0.016)		(0.015)		
Diversification	0.128**	0.457**	0.126**	0.122**		0.123**		
	(0.060)	(0.206)	(0.057)	(0.060)		(0.057)		
Lower profitability	0.002	0.134	0.005	0.006		0.006		
	(0.055)	(0.172)	(0.055)	(0.055)		(0.055)		
Portfolio 2								
Level of knowledge	0.020	0.060	0.020		0.020		0.021	
	(0.023)	(0.059)	(0.023)		(0.022)		(0.023)	
Informal knowledge	0.042	0.154*	0.043		0.042		0.043	
	(0.036)	(0.089)	(0.035)		(0.036)		(0.036)	
Experience	−0.006**	−0.005	−0.006**		−0.006**		−0.006**	
	(0.003)	(0.007)	(0.003)		(0.003)		(0.003)	
Farm household	−0.006	0.026	−0.006		−0.006		−0.007	
	(0.013)	(0.051)	(0.013)		(0.013)		(0.013)	
Diversification	0.156**	0.313	0.156**		0.158**		0.159**	
	(0.070)	(0.201)	(0.069)		(0.070)		(0.069)	
Lower profitability	−0.035	−0.053	−0.036		−0.036		−0.038	
	(0.066)	(0.168)	(0.066)		(0.066)		(0.066)	
Portfolio 3								
Level of knowledge	−0.003	0.080		−0.004	−0.001			−0.003
	(0.011)	(0.061)		(0.011)	(0.011)			(0.011)
Informal knowledge	0.056***	0.382***		0.058***	0.058***			0.060***
	(0.019)	(0.090)		(0.019)	(0.019)			(0.020)
Experience	−0.001	−0.001		−0.001	−0.001			−0.001
	(0.001)	(0.007)		(0.001)	(0.001)			(0.001)
Farm household	−0.002	0.062		−0.003	−0.002			−0.002
	(0.006)	(0.045)		(0.004)	(0.007)			(0.005)
Diversification	0.051	0.194		0.050	0.059			0.055
	(0.037)	(0.211)		(0.037)	(0.038)			(0.038)
Lower profitability	0.009	0.071		0.019	0.006			0.017
	(0.032)	(0.166)		(0.033)	(0.035)			(0.035)
ρ_{12}	0.270*	0.232**	0.250*					
	(0.142)	(0.091)	(0.148)					
ρ_{13}	0.743***	0.403***		0.751***				
	(0.120)	(0.064)		(0.118)				
ρ_{23}	0.567***	0.315***			0.576***			
	(0.145)	(0.080)			(0.158)			
Log likelihood	−191.574	−829.330	−165.981	−97.397	−130.340	−68.095	−99.110	−35.631
Wald test (χ^2)	58.27	81.16	44.26	37.17	31.67	25.80	13.99	16.89
Wald test (df)	18	18	12	12	12	6	6	6
P value	0.000***	0.000***	0.000***	0.000***	0.001***	0.000***	0.029**	0.010***
Likelihood ratio test (χ^2)	22.524		2.448	12.658	8.802			
Likelihood ratio test (df)	3		1	1	1			
P value	0.000***		0.118	0.000***	0.003***			
Observations	180	180	180	180	180	180	180	180

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. [a] For the ordered multivariate probit model, we present parameter estimates for the sake of brevity as presenting APEs would require a separate category for each outcome group. Hence, we cannot directly compare the parameters of this model to the other APEs. However, the direction and significance can still be compared.

Table A6
Average partial effects of the different probit specifications which include land as additional control variable. Robust Newey-West standard errors are presented in parentheses.

	Multivariate probit	Ordered multivariate probit[a]	Bivariate probit; portfolio 1 and 2	Bivariate probit; portfolio 1 and 3	Bivariate probit; portfolio 2 and 3	Univariate probit, portfolio 1	Univariate probit, portfolio 2	Univariate probit, portfolio 3
Portfolio 1								

(continued on next page)

Table A6 (*continued*)

	Multivariate probit	Ordered multivariate probit[a]	Bivariate probit; portfolio 1 and 2	Bivariate probit; portfolio 1 and 3	Bivariate probit; portfolio 2 and 3	Univariate probit, portfolio 1	Univariate probit, portfolio 2	Univariate probit, portfolio 3
Level of knowledge	0.056***	0.201***	0.055***	0.052***		0.054***		
	(0.018)	(0.070)	(0.018)	(0.017)		(0.018)		
Informal knowledge	0.077***	0.482***	0.077**	0.082***		0.077**		
	(0.029)	(0.118)	(0.031)	(0.030)		(0.031)		
Experience	−0.000	−0.008	−0.000	−0.000		−0.000		
	(0.002)	(0.009)	(0.002)	(0.002)		(0.002)		
Farm household	0.001	0.070*	0.000	−0.000		0.000		
	(0.013)	(0.042)	(0.013)	(0.012)		(0.012)		
Diversification	0.167**	0.475*	0.155**	0.155**		0.151**		
	(0.081)	(0.262)	(0.070)	(0.076)		(0.070)		
Lower profitability	0.019	0.179	0.025	0.021		0.027		
	(0.064)	(0.221)	(0.063)	(0.064)		(0.063)		
Land	−0.000	0.001	−0.000	−0.000		−0.000		
	(0.000)	(0.002)	(0.000)	(0.000)		(0.000)		
Portfolio 2								
Level of knowledge	0.019	−0.000	0.018		0.019		0.018	
	(0.027)	(0.070)	(0.027)		(0.027)		(0.027)	
Informal knowledge	0.055	0.203*	0.056		0.056		0.056	
	(0.045)	(0.120)	(0.044)		(0.045)		(0.044)	
Experience	−0.002	0.002	−0.002		−0.002		−0.002	
	(0.004)	(0.009)	(0.004)		(0.004)		(0.004)	
Farm household	0.007	0.103**	0.007		0.006		0.006	
	(0.014)	(0.047)	(0.014)		(0.014)		(0.014)	
Diversification	−0.013	0.168	−0.013		−0.012		−0.011	
	(0.099)	(0.241)	(0.100)		(0.100)		(0.100)	
Lower profitability	−0.023	0.020	−0.024		−0.025		−0.025	
	(0.083)	(0.223)	(0.083)		(0.083)		(0.083)	
Land	0.001	0.001	0.001		0.001		0.001	
	(0.001)	(0.001)	(0.001)		(0.001)		(0.001)	
Portfolio 3								
Level of knowledge	−0.004	0.096		−0.005	0.002			−0.001
	(0.014)	(0.076)		(0.011)	(0.012)			(0.011)
Informal knowledge	0.074***	0.409***		0.078***	0.080***			0.084***
	(0.021)	(0.111)		(0.023)	(0.023)			(0.025)
Experience	−0.002	0.001		−0.000	−0.000			0.000
	(0.002)	(0.009)		(0.002)	(0.002)			(0.001)
Farm household	−0.003	0.073		−0.001	−0.004			−0.002
	(0.004)	(0.053)		(0.006)	(0.005)			(0.006)
Diversification	0.061	−0.114		0.050	0.069			0.062
	(0.049)	(0.315)		(0.043)	(0.045)			(0.046)
Lower profitability	0.020	−0.097		0.042	0.007			0.030
	(0.033)	(0.220)		(0.037)	(0.035)			(0.038)
Land	0.000	0.000		0.000	0.000			0.000
	(0.000)	(0.001)		(0.000)	(0.000)			(0.000)
ρ_{12}	0.113	0.168	0.133					
	(0.207)	(0.105)	(0.201)					
ρ_{13}	0.852***	0.460***		0.762***				
	(0.152)	(0.074)		(0.140)				
ρ_{23}	0.535***	0.277**			0.545**			
	(0.172)	(0.104)			(0.212)			
Log likelihood	−124.451	−537.017	−111.192	−57.542	−85.916	−42.178	−69.479	−18.552
Wald test (χ^2)	58.01	67.68	24.21	38.88	34.87	15.57	6.84	23.51
Wald test (df)	21	21	14	14	14	7	7	7
P value	0.000	0.000	0.043	0.000	0.002	0.029	0.057	0.001
Likelihood ratio test (χ^2)	9.484		0.428	5.874	4.230			
Likelihood ratio test (df)	3		1	1	1			
P value	0.024		0.513	0.015	0.040			
Observations	120	120	120	120	120	120	120	120

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. [a] For the ordered multivariate probit model, we present parameter estimates for the sake of brevity as presenting APEs would require a separate category for each outcome group. Hence, we cannot directly compare the parameters of this model to the other APEs. However, the direction and significance can still be compared.

Table A7
Reflective model assessment: Cronbach's alpha, composite reliability, average variance explained for level of knowledge

	Cronbach's alpha	Composite reliability	Average variance explained
All SAP	0.915	0.923	0.857
Portfolio 1	0.915	0.920	0.853
Portfolio 2	0.915	0.959	0.924
Portfolio 3	0.915	0.917	0.848

Table A8
Indicator loadings for the reflective constructs (level of knowledge)

	Indicator loadings	
	$Know_1$	$Know_2$
All SAP	0.841	0.909
Portfolio 1	0.855	0.907
Portfolio 2	0.741	0.913
Portfolio 3	0.877	0.962

Table A9
Heterotrait-Monotrait (HTMT) ratios for the general model

	Level of knowledge	Informal knowledge	Lack of PBC	Risk perception	Perceived benefits	Number of SAP
Level of knowledge						
Informal knowledge	0.088					
Lack of PBC	0.599	0.083				
Risk perception	0.255	0.178	0.309			
Perceived benefits	0.177	0.297	0.142	0.249		
Number of SAP	0.233	0.413	0.161	0.190	0.250	

Table A10
Heterotrait-Monotrait (HTMT) ratios for the model explaining portfolio 1

	Level of knowledge	Informal knowledge	Lack of PBC	Risk perception	Perceived benefits	Portfolio 1
Level of knowledge						
Informal knowledge	0.088					
Lack of PBC	0.599	0.083				
Risk perception	0.255	0.178	0.309			
Perceived benefits	0.095	0.309	0.113	0.108		
Portfolio 1	0.268	0.409	0.243	0.233	0.116	

Table A11
Heterotrait-Monotrait (HTMT) ratios for the model explaining portfolio 2

	Level of knowledge	Informal knowledge	Lack of PBC	Risk perception	Perceived benefits	Portfolio 2
Level of knowledge						
Informal knowledge	0.088					
Lack of PBC	0.599	0.083				
Risk perception	0.255	0.145	0.233			
Perceived benefits	0.177	0.307	0.156	0.253		
Portfolio 2	0.101	0.158	0.085	0.063	0.187	

Table A12
Heterotrait-Monotrait (HTMT) ratios for the model explaining portfolio 3

	Level of knowledge	Informal knowledge	Lack of PBC	Risk perception	Perceived benefits	Portfolio 3
Level of knowledge						
Informal knowledge	0.088					
Lack of PBC	0.599	0.083				

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Table A12 (*continued*)

	Level of knowledge	Informal knowledge	Lack of PBC	Risk perception	Perceived benefits	Portfolio 3
Risk perception	0.292	0.204	0.351			
Perceived benefits	0.177	0.297	0.142	0.252		
Portfolio 3	0.136	0.333	0.019	0.174	0.312	

Table A13
Formative measurement model assessment: Redundancy analysis for risk perception (RP) and perceived benefits (PB) under different model specifications

Formative construct	Reflective construct	R^2
RP (2 item)	Statements related to (i) climate change and (ii) consumer health as risk perception	0.613
RP (3 item)	Statements related to (i) climate change and (ii) consumer health as risk perception	0.722
PB (2 item)	Statements related to (i) reduced fertiliser usage and (ii) soil quality as benefits	0.700
PB (3 item)	Statement related to reduced fertiliser usage as benefits	0.517
PB (4 item)	Statement related to reduced fertiliser usage as benefits	0.523

Table A14
Formative model assessment: outer weights, outer loadings, and variance inflation factors (VIFs)

	All SAP jointly			Portfolio 1			Portfolio 2			Portfolio 3		
	Outer weight	Outer loadings	VIF	Outer weight	Outer loadings	VIF	Outer weight	Outer loadings	VIF	Outer weight	Outer loadings	VIF
Risk perception (RP)												
RP_1	0.393	0.608**	1.209	0.467	0.658***	1.209				0.566	0.699**	1.119
RP_2	0.214	0.588***	1.518	0.458	0.715***	1.518	0.349	0.598*	1.406			
RP_3	0.419	0.665***	1.437	0.352	0.649***	1.437	0.467	0.655**	1.406	0.431	0.621**	1.119
Perceived benefits (PB)												
PB_1	0.039	0.623***	2.654	0.167	0.685**	2.317	0.116	0.568**	2.351	0.211	0.520***	2.654
PB_2	0.491*	0.731***	2.553	0.690	0.820***	2.317	0.245	0.624**	2.531	0.345	0.589***	2.553
PB_3	0.332	0.623***	1.471							0.678***	0.830***	1.471
PB_4	0.288	0.655***	1.516				0.584*	0.748***	1.374	0.298	0.669***	1.516

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A15
Variance inflation factors (VIFs) of the structural model for different model specifications

	All SAP	Portfolio 1	Portfolio 2	Portfolio 3
Level of knowledge	1.516	1.503	1.528	1.520
Informal knowledge	1.149	1.159	1.120	1.099
PBC	1.541	1.553	1.524	1.538
Risk perception	1.127	1.107	1.144	1.103
Benefits	1.167	1.145	1.222	1.108

Table A16
f^2 effect sizes for explaining the number of SAP in a portfolio

	All SAP	Portfolio 1	Portfolio 2	Portfolio 3
Level of knowledge	0.035	0.022	0.006	0.035
Informal knowledge	0.123	0.153	0.008	0.068
PBC	0.000	0.008	0.001	0.012
Risk perception	0.011	0.008	0.006	0.095
Benefits	0.038	0.001	0.036	0.013

Table A17
PLS-SEM path coefficients under different model specifications for the general model. 95% bootstrapped confidence intervals (CI) are presented in squared brackets.

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.199**	[0.009; 0.389]	0.199***	[0.049; 0.344]	0.188*	[-0.006; 0.382]	0.183**	[0.035; 0.329]
Informal knowledge	0.319***	[0.190; 0.438]	0.394***	[0.268; 0.508]	0.392***	[0.266; 0.507]	0.382***	[0.256; 0.498]
Lack of PBC	−0.019	[-0.218; 0.171]			−0.019	[-0.213; 0.171]		
Risk perception	−0.123*	[-0.248; 0.015]					−0.104	[-0.231; 0.032]
Benefits	0.209**	[0.040; 0.358]						
Knowledge*Informal knowledge								
AIC	−38.265		−36.710		−34.822		−35.659	
BIC	−19.108		−27.131		−22.050		−22.887	
R^2	0.242		0.209		0.209		0.213	
Adjusted R^2	0.220		0.200		0.196		0.200	

	Model 5		Model 6		Model 7		Model 8	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.226***	[0.073; 0.371]	0.181*	[-0.010; 0.373]	0.206**	[0.010; 0.397]	0.209***	[0.061; 0.355]
Informal knowledge	0.338***	[0.212; 0.456]	0.381***	[0.255; 0.497]	0.335***	[0.208; 0.453]	0.320***	[0.194; 0.439]
Lack of PBC			−0.004	[-0.199; 0.185]	−0.036	[-0.238; 0.156]		
Risk perception			−0.103	[-0.231; 0.038]			−0.125*	[-0.251; 0.010]
Benefits	0.195**	[0.040; 0.335]			0.197**	[0.036; 0.343]	0.208**	[0.045; 0.352]
Knowledge*Informal knowledge								
AIC	−40.056		−33.690		−38.313		−40.183	
BIC	−27.284		−17.725		−22.349		−24.218	
R^2	0.233		0.213		0.234		0.242	
Adjusted R^2	0.220		0.195		0.216		0.225	

	Model 9		Model 10		Model 11	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge			0.219**	[0.014; 0.418]	0.202**	[0.011; 0.392]
Informal knowledge	0.329***	[0.200; 0.446]			0.315***	[0.177; 0.437]
Lack of PBC	−0.131*	[-0.280; 0.020]	−0.033	[-0.245; 0.172]	−0.018	[-0.218; 0.174]
Risk perception	−0.133*	[-0.256; 0.008]	−0.166**	[-0.295; −0.023]	−0.122*	[-0.249; 0.017]
Benefits	0.198**	[0.038; 0.345]	0.304**	[0.132; 0.448]	0.210**	[0.039; 0.359]
Knowledge*Informal knowledge					−0.013	[-0.164; 0.135]
AIC	−34.707		−19.269		−36.268	
BIC	−18.742		−3.304		−13.918	
R^2	0.216		0.149		0.242	
Adjusted R^2	0.198		0.129		0.216	

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. The following PLS-SEM settings were used: maximum number of iterations is set to 300 with a stop criterion of 10^{-7} and 10,000 bootstrap repetitions using the path weighting method. The confidence intervals are based on the bootstrapped mean and standard errors. For some path coefficients slightly asymmetric as a result of applying a non-parametric method.

Table A18
PLS-SEM path coefficients under different model specifications for the model explaining portfolio 1. 95% bootstrapped confidence intervals (CI) are presented in squared brackets.

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.160*	[0.036; 0.354]	0.234***	[0.091; 0.371]	0.167*	[-0.035; 0.362]	0.212***	[0.071; 0.350]
Informal knowledge	0.357***	[0.228; 0.476]	0.388***	[0.265; 0.500]	0.384***	[0.263; 0.495]	0.373***	[0.250; 0.487]

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Table A18 (*continued*)

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Lack of PBC	−0.097	[-0.294; 0.089]			−0.113	[-0.312; 0.075]		
Risk perception	−0.109*	[-0.234; 0.017]					−0.119*	[-0.243; 0.007]
Benefits	0.042	[-0.103; 0.172]						
Knowledge*Informal knowledge								
AIC	−36.961		−39.272		−39.533		−39.191	
BIC	−17.804		−29.693		−26.761		−26.420	
R^2	0.236		0.222		0.230		0.230	
Adjusted R^2	0.214		0.213		0.217		0.216	
	Model 5		Model 6		Model 7		Model 8	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.236***	[0.094; 0.373]	0.159*	[-0.039; 0.352]	0.169*	[-0.033; 0.362]	0.215***	[0.075; 0.351]
Informal knowledge	0.379***	[0.252; 0.496]	0.370***	[0.248; 0.483]	0.373***	[0.245; 0.489]	0.361***	[0.231; 0.478]
Lack of PBC			−0.094	[-0.292; 0.091]	−0.116	[-0.315; 0.073]		
Risk perception			−0.107*	[-0.230; 0.017]			−0.122*	[-0.248; 0.005]
Benefits	0.031	[-0.111; 0.162]			0.036	[-0.108; 0.167]	0.038	[-0.104; 0.168]
Knowledge*Informal knowledge								
AIC	−37.277		−38.850		−37.585		−37.242	
BIC	−24.506		−22.885		−21.620		−21.277	
R^2	0.222		0.235		0.230		0.230	
Adjusted R^2	0.209		0.218		0.212		0.212	
	Model 9		Model 10		Model 11			
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI		
Level of knowledge			0.176*	[-0.031; 0.382]	0.161*	[-0.036; 0.355]		
Informal knowledge	0.363***	[0.238; 0.478]			0.355***	[0.221; 0.475]		
Lack of PBC	−0.188***	[-0.320; −0.050]	−0.112	[-0.324; 0.089]	−0.100	[-0.299; 0.090]		
Risk perception	−0.119*	[-0.245; 0.008]	−0.159**	[-0.293; −0.026]	−0.111*	[-0.239; 0.018]		
Benefits	0.040	[-0.106; 0.171]	0.142	[-0.069; 0.285]	0.045	[-0.105; 0.177]		
Knowledge*Informal knowledge					0.011	[-0.121; 0.139]		
AIC	−35.446		−13.365		−34.991			
BIC	−19.481		2.600		−12.641			
R^2	0.219		0.119		0.236			
Adjusted R^2	0.201		0.099		0.209			

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. The following PLS-SEM settings were used: maximum number of iterations is set to 300 with a stop criterion of 10^{-7} and 10,000 bootstrap repetitions using the path weighting method. The confidence intervals are based on the bootstrapped mean and standard errors. For some path coefficients slightly asymmetric as a result of applying a non-parametric method.

Table A19
PLS-SEM path coefficients under different model specifications for the model explaining portfolio 2. 95% bootstrapped confidence intervals (CI) are presented in squared brackets.

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.100	[-0.070; 0.280]	0.100	[-0.065; 0.254]	0.079	[-0.095; 0.259]	0.095	[-0.065; 0.246]
Informal knowledge	0.095	[-0.040; 0.223]	0.149**	[0.012; 0.280]	0.148**	[0.010; 0.281]	0.145**	[0.006; 0.279]
Lack of PBC	−0.052	[-0.237; 0.125]			−0.037	[-0.221; 0.138]		
Risk perception	−0.077	[-0.231; 0.118]					−0.044	[-0.197; 0.152]
Benefits	0.219*	[-0.050; 0.366]						
Knowledge*Informal knowledge								

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Table A19 (*continued*)

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
AIC	−1.565		−0.985		0.894		0.906	
BIC	17.593		8.594		13.666		13.678	
R^2	0.067		0.032		0.033		0.033	
Adjusted R^2	0.040		0.021		0.017		0.016	
	Model 5		**Model 6**		**Model 7**		**Model 8**	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.133	[-0.027; 0.289]	0.077	[-0.095; 0.255]	0.101	[-0.069; 0.286]	0.127	[-0.028; 0.281]
Informal knowledge	0.107	[-0.026; 0.233]	0.145**	[0.003; 0.279]	0.104	[-0.032; 0.232]	0.097	[-0.035; 0.222]
Lack of PBC			−0.032	[-0.218; 0.145]	−0.060	[-0.242; 0.118]		
Risk perception			−0.041	[-0.196; 0.157]			−0.080	[-0.233; 0.114]
Benefits	0.201*	[-0.058; 0.343]			0.206*	[-0.057; 0.353]	0.215*	[-0.052; 0.357]
Knowledge*Informal knowledge								
AIC	−4.225		2.809		−2.506		−3.379	
BIC	8.547		18.774		13.459		12.586	
R^2	0.060		0.034		0.062		0.066	
Adjusted R^2	0.044		0.012		0.040		0.045	

	Model 9		Model 10		Model 11	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge			0.105	[-0.063; 0.291]	0.101	[-0.068; 0.282]
Informal knowledge	0.098	[-0.036; 0.225]			0.094	[-0.047; 0.224]
Lack of PBC	−0.076	[-0.232; 0.120]	−0.058	[-0.239; 0.119]	−0.058	[-0.244; 0.123]
Risk perception	−0.099	[-0.257; 0.057]	−0.087	[-0.241; 0.110]	−0.078	[-0.235; 0.118]
Benefits	0.213*	[-0.031; 0.358]	0.240*	[-0.037; 0.388]	0.221*	[-0.042; 0.367]
Knowledge*Informal knowledge					0.028	[-0.137; 0.193]
AIC	−2.350		−2.208		0.139	
BIC	13.615		13.757		22.489	
R^2	0.061		0.060		0.069	
Adjusted R^2	0.040		0.038		0.036	

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. The following PLS-SEM settings were used: maximum number of iterations is set to 300 with a stop criterion of 10^{-7} and 10,000 bootstrap repetitions using the path weighting method. The confidence intervals are based on the bootstrapped mean and standard errors. For some path coefficients slightly asymmetric as a result of applying a non-parametric method.

Table A20

PLS-SEM path coefficients under different model specifications for the model explaining portfolio 3. 95% bootstrapped confidence intervals (CI) are presented in squared brackets.

	Full model		Model 2		Model 3		Model 4	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.201**	[0.015; 0.393]	0.111	[-0.038; 0.260]	0.173*	[-0.005; 0.365]	0.099*	[-0.047; 0.249]
Informal knowledge	0.237***	[0.099; 0.367]	0.322***	[0.182; 0.451]	0.324***	[0.181; 0.455]	0.312***	[0.172; 0.444]
Lack of PBC	0.107	[-0.082; 0.303]			0.108	[-0.067; 0.293]		
Risk perception	−0.112	[-0.246; 0.045]					−0.082	[-0.215; 0.090]
Benefits	0.307***	[0.166; 0.438]						
Knowledge*Informal knowledge								
AIC	−30.842		−18.312		−17.698		−16.954	
BIC	−11.684		−8.733		−4.926		−4.182	
R^2	0.211		0.122		0.131		0.125	
Adjusted R^2	0.188		0.112		0.116		0.110	
	Model 5		**Model 6**		**Model 7**		**Model 8**	

(*continued on next page*)

Table A20 (*continued*)

	Model 5		Model 6		Model 7		Model 8	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge	0.155**	[0.003; 0.307]	0.167*	[-0.007; 0.357]	0.207**	[0.015; 0.403]	0.142*	[-0.004; 0.292]
Informal knowledge	0.250***	[0.115; 0.377]	0.313***	[0.170; 0.446]	0.251***	[0.114; 0.381]	0.236***	[0.098; 0.365]
Lack of PBC			0.122	[-0.055; 0.309]	0.090	[-0.100; 0.286]		
Risk perception			−0.094	[-0.229; 0.080]			−0.102	[-0.237; 0.053]
Benefits	0.300***	[0.161; 0.432]			0.298***	[0.157; 0.433]	0.309***	[0.169; 0.439]
Knowledge*Informal knowledge								
AIC	−31.327		−16.735		−30.494		−31.088	
BIC	−18.556		−0.770		−14.530		−15.123	
R^2	0.194		0.135		0.201		0.201	
Adjusted R^2	0.180		0.116		0.182		0.183	

	Model 9		Model 10		Model 11	
	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI	Bootstrapped mean	95% CI
Level of knowledge			0.219**	[0.019; 0.420]	0.205**	[0.016; 0.399]
Informal knowledge	0.248***	[0.109; 0.379]			0.229***	[0.086; 0.362]
Lack of PBC	−0.002	[-0.165; 0.158]	0.098	[-0.107; 0.308]	0.116	[-0.075; 0.314]
Risk perception	−0.122	[-0.254; 0.045]	−0.141*	[-0.275; 0.034]	−0.106	[-0.239; 0.050]
Benefits	0.291***	[0.150; 0.426]	0.367***	[0.230; 0.495]	0.302***	[0.155; 0.438]
Knowledge*Informal knowledge					−0.072	[-0.217; 0.073]
AIC	−27.398		−20.882		−29.821	
BIC	−11.433		−4.917		−7.470	
R^2	0.183		0.157		0.215	
Adjusted R^2	0.164		0.138		0.188	

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. The following PLS-SEM settings were used: maximum number of iterations is set to 300 with a stop criterion of 10^{-7} and 10,000 bootstrap repetitions using the path weighting method. The confidence intervals are based on the bootstrapped mean and standard errors. For some path coefficients slightly asymmetric as a result of applying a non-parametric method.

References

Agrimatie, 2022. Arbeidsinzet en – productiviteit akkerbouw. https://www.agrimatie.nl/themaResultaat.aspx?subpubID=2232&sectorID=2233&themaID=2264&indicatorID=2078. (Accessed 20 March 2023).

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179.

Ajzen, I., 2002. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. J. Appl. Soc. Psychol. 32 (4), 665–683.

Ammann, J., Walter, A., El Benni, N., 2022. Adoption and perception of farm management information systems by future Swiss farm managers – an online study. J. Rural Stud. 89, 298–305.

Arbuckle Jr., J.G., Morton, L.W., Hobbs, J., 2015. Understanding farmer perspectives on climate change adaptation and mitigation: the roles of trust in sources of climate information, climate change beliefs, and perceived risk. Environ. Behav. 47 (2), 205–234.

Baumgart-Getz, A., Prokopy, L.S., Floress, K., 2012. Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. J. Environ. Manag. 96 (1), 17–25.

Bopp, C., Engler, A., Poortvliet, P.M., Jara-Rojas, R., 2019. The role of farmers' intrinsic motivation in the effectiveness of policy incentives to promote sustainable agricultural practices. J. Environ. Manag. 244 (1), 320–327.

Caffaro, F., Micheletti Cremasco, M., Roccato, M., Cavallo, E., 2020. Drivers of farmers' intention to adopt technological innovations in Italy: the role of information sources, perceived usefulness, and perceived ease of use. J. Rural Stud. 76, 264–271.

Cappellari, L., Jenkins, S.P., 2003. Multivariate probit regression using simulated maximum likelihood. STATA J.: Promoting communications on statistics and Stata 3 (3), 278–294.

CBS, 2022. Statline – Online Database for Dutch Statistics. https://opendata.cbs.nl/statline/#/CBS/nl/. (Accessed 20 March 2023).

Claudy, M.C., Garcia, R., O'Driscoll, A., 2014. Consumer resistance to innovation—a behavioral reasoning perspective. J. Acad. Market. Sci. 43 (4), 528–544.

Dessart, F.J., Barreiro-Hurlé, J., van Bavel, R., 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Eur. Rev. Agric. Econ. 46 (3), 417–471.

Diamantopoulos, A., Siguaw, J.A., 2006. Formative versus reflective indicators in organizational measure development: a comparison and empirical illustration. Br. J. Manag. 17 (4), 263–282.

Dicks, L.V., Rose, D.C., Ang, F., Aston, S., Birch, A.N.E., Boatman, N., Bowles, E.L., Chadwick, D., Dinsdale, A., Durham, S., Elliott, J., Firbank, L., Humphreys, S., Jarvis, P., Jones, D., Kindred, D., Knight, S.M., Lee, M.R.F., Leifert, C., Lobley, M., Matthews, K., Midmer, A., Moore, M., Morris, C., Mortimer, S., Murray, T.C., Norman, K., Ramsden, S., Roberts, D., Smith, L.G., Soffe, R., Stoate, C., Taylor, B., Tinker, D., Topliff, M., Wallace, J., Williams, P., Wilson, P., Winter, M., Sutherland, W.J., 2019. What agricultural practices are most likely to deliver "sustainable intensification" in the UK? Food Energy Secur. 8 (1), e00148.

D'Emden, F.H., Llewellyn, R.S., Burton, M.P., 2008. Factors influencing adoption of conservation tillage in Australian cropping regions. Aust. J. Agric. Resour. Econ. 52 (2), 169–182.

European Commission, 2020. A Farm to Fork Strategy for a Fair, Healthy and Environmentally-Friendly Food System (Brussels).

FAO, 1989. In: Nations, F.A.O. of the United Nations. (Ed.), Sustainable Development and Natural Resources Management (Rome).

Fielding, K.S., Terry, D.J., Masser, B.M., Hogg, M.A., 2008. Integrating social identity theory and the theory of planned behaviour to explain decisions to engage in sustainable agricultural practices. Br. J. Soc. Psychol. 47 (Pt 1), 23–48.

Fishbein, M., Ajzen, I., 2011. Predicting and Changing Behavior - the Reasoned Action Approach.

Foguesatto, C.R., Borges, J.A.R., Machado, J.A.D., 2020. A review and some reflections on farmers' adoption of sustainable agricultural practices worldwide. Sci. Total Environ. 729, 138831.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2016. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2 ed. SAGE Publications, London.

Hardaker, J.B., Lien, G., 2010. Probabilities for decision analysis in agriculture and rural resource economics: the need for a paradigm change. Agric. Syst. 103 (6), 345–350.

Kallas, Z., Serra, T., Gil, J.M., 2010. Farmers' objectives as determinants of organic farming adoption: the case of Catalonian vineyard production. Agric. Econ. 41 (5), 409–423.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. Land Use Pol. 42, 400–411.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: a review and synthesis of recent research. Food Pol. 32 (1), 25–48.
Kock, N., Hadaya, P., 2018. Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods. Inf. Syst. J. 28 (1), 227–261.
Kuhfuss, L., Préget, R., Thoyer, S., Hanley, N., Coent, P.L., Désolé, M., 2016. Nudges, social norms, and permanence in agri-environmental schemes. Land Econ. 92 (4), 641–655.
Lamkowsky, M., Oenema, O., Meuwissen, M.P.M., Ang, F., 2021. Closing productivity gaps among Dutch dairy farms can boost profit and reduce nitrogen pollution. Environ. Res. Lett. 16 (12).
Läpple, D., Rensburg, T.V., 2011. Adoption of organic farming: are there differences between early and late adoption? Ecol. Econ. 70 (7), 1406–1414.
Li, Q., Steeg, G.V., Yu, S., Malo, J., 2022. Functional connectome of the human brain with total correlation. Entropy 24 (12).
Llewellyn, R.S., 2007. Information quality and effectiveness for more rapid adoption decisions by farmers. Field Crop. Res. 104 (1–3), 148–156.
Massfeller, A., Meraner, M., Hüttel, S., Uehleke, R., 2022. Farmers' Acceptance of Results-Based Agri-Environmental Schemes: A German Perspective. Land Use Policy 120.
Meuwissen, M.P.M., Feindt, P.H., Spiegel, A., Termeer, C.J.A.M., Mathijs, E., Mey, Y.d., Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., Ciechomska, A., Accatino, F., Kopainsky, B., Poortvliet, P.M., Candel, J. J.L., Maye, D., Severini, S., Senni, S., Soriano, B., Lagerkvist, C.-J., Peneva, M., Gavrilescu, C., Reidsma, P., 2019. A framework to assess the resilience of farming systems. Agric. Syst. 176, 102656.
Michie, S., van Stralen, M.M., West, R., 2011. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. Implement. Sci. 6, 42.
Pavlis, E.S., Terkenli, T.S., Kristensen, S.B.P., Busck, A.G., Cosor, G.L., 2016. Patterns of agri-environmental scheme participation in Europe: indicative trends from selected case studies. Land Use Pol. 57, 800–812.
Pe'er, G., Bonn, A., Bruelheide, H., Dieker, P., Eisenhauer, N., Feindt, P.H., Hagedorn, G., Hansjurgens, B., Herzon, I., Lomba, A., Marquard, E., Moreira, F., Nitsch, H., Oppermann, R., Perino, A., Roder, N., Schleyer, C., Schindler, S., Wolf, C., Zinngrebe, Y., Lakner, S., 2020. Action needed for the EU Common Agricultural Policy to address sustainability challenges. People and Nature 2 (2), 305–316.
Piñeiro, V., Arias, J., Dürr, J., Elverdin, P., Ibáñez, A.M., Kinengyere, A., Opazo, C.M., Owoo, N., Page, J.R., Prager, S.D., Torero, M., 2020. A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. Nat. Sustain. 3 (10), 809–820.
Prokopy, L.S., Floress, K., Klotthor-Weinkauf, D., Baumgart-Getz, A., 2008. Determinants of agricultural best management practice adoption: evidence from the literature. J. Soil Water Conserv. 63 (5), 300–311.
Ray, S., Danks, N.P., Valdez, A.C., Estrada, J.M.V., Uanhoro, J., Nakayama, J., Koyan, L., Burbach, L., Nejar, A.H.C., Adler, S., 2021. Seminr: Building and Estimating Structural Equation Models.
Rockstrom, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., Smith, J., 2017. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio 46 (1), 4–17.
Rodriguez, J.M., Molnar, J.J., Fazio, R.A., Sydnor, E., Lowe, M.J., 2008. Barriers to adoption of sustainable agriculture practices: change agent perspectives. Renew. Agric. Food Syst. 24 (1), 60–71.
Rogers, E., 1962. Diffusion of Innovations. The Free Press, New York.
Rooney, J.P.K., 2021. Rcorex: Discover Latent Structure in High Dimensional Data.
Slijper, T., de Mey, Y., Poortvliet, P.M., Meuwissen, M.P.M., 2020. From risk behavior to perceived farm resilience: a Dutch case study. Ecol. Soc. 25 (4).
Slijper, T., Urquhart, J., Poortvliet, P.M., Soriano, B., Meuwissen, M.P.M., 2022. Exploring how social capital and learning are related to the resilience of Dutch arable farmers. Agric. Syst. 198.
Spiegal, S., Bestelmeyer, B.T., Archer, D.W., Augustine, D.J., Boughton, E.H., Boughton, R.K., Cavigelli, M.A., Clark, P.E., Derner, J.D., Duncan, E.W., Hapeman, C. J., Harmel, R.D., Heilman, P., Holly, M.A., Huggins, D.R., King, K., Kleinman, P.J.A., Liebig, M.A., Locke, M.A., McCarty, G.W., Millar, N., Mirsky, S.B., Moorman, T.B., Pierson, F.B., Rigby, J.R., Robertson, G.P., Steiner, J.L., Strickland, T.C., Swain, H. M., Wienhold, B.J., Wulfhorst, J.D., Yost, M.A., Walthall, C.L., 2018. Evaluating strategies for sustainable intensification of US agriculture through the Long-Term Agroecosystem Research network. Environ. Res. Lett. 13 (3).
Spiegel, A., Soriano, B., de Mey, Y., Slijper, T., Urquhart, J., Bardaji, I., Vigani, M., Severini, S., Meuwissen, M.P.M., 2020. Risk management and its role in enhancing perceived resilience capacities of farms and farming systems in Europe. EuroChoices 19 (2), 45–53.
Šūmane, S., Kunda, I., Knickel, K., Strauss, A., Tisenkopfs, T., Rios, I.d.I., Rivera, M., Chebach, T., Ashkenazy, A., 2018. Local and farmers' knowledge matters! How integrating informal and formal knowledge enhances sustainable and resilient agriculture. J. Rural Stud. 59, 232–241.
Tensi, A.F., Ang, F., Van der Fels-Klerx, H.J., 2022. Behavioural Drivers and Barriers for Adopting Microbial Applications in Arable Farming: Evidence from the Netherlands and Germany. Technological Forecasting & Social Change.
Thomas, E., Riley, M., Spees, J., 2020. Knowledge flows: farmers' social relations and knowledge sharing practices in 'Catchment Sensitive Farming'. Land Use Pol. 90, 104254.
Toma, L., Mathijs, E., 2007. Environmental risk perception, environmental concern and propensity to participate in organic farming programmes. J. Environ. Manag. 83 (2), 145–157.
Trujillo-Barrera, A., Pennings, J.M.E., Hofenk, D., 2016. Understanding producers' motives for adopting sustainable practices: the role of expected rewards, risk perception and risk tolerance. Eur. Rev. Agric. Econ. 43 (3), 359–382.
van Grinsven, H.J.M., van Eerdt, M.M., Westhoek, H., Kruitwagen, S., 2019. Benchmarking eco-efficiency and footprints of Dutch agriculture in European context and implications for policies for climate and environment. Front. Sustain. Food Syst. 3.
Vanslembrouck, I., Huylenbroeck, G., Verbeke, W., 2002. Determinants of the willingness of Belgian farmers to participate in agri-environmental measures. J. Agric. Econ. 53 (3), 489–511.
Ver Steeg, G., Galstyan, A., 2014. Discovering structure in high-dimensional data through correlation explanation. Adv. Neural Inf. Process. Syst. 27.
Villanueva, A.J., Rodríguez-Entrena, M., Arriaza, M., Gómez-Limón, J.A., 2016. Heterogeneity of farmers' preferences towards agri-environmental schemes across different agricultural subsystems. J. Environ. Plann. Manag. 60 (4), 684–707.
Weltin, M., Zasada, I., Piorr, A., Debolini, M., Geniaux, G., Moreno Perez, O., Scherer, L., Tudela Marco, L., Schulp, C.J.E., 2018. Conceptualising fields of action for sustainable intensification – a systematic literature review and application to regional case studies. Agric. Ecosyst. Environ. 257, 68–80.
Weltin, M., Zasada, I., Hüttel, S., 2021. Relevance of portfolio effects in adopting sustainable farming practices. J. Clean. Prod. 313.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. The MIT Press, London, England.
Yeboah, F.K., Lupi, F., Kaplowitz, M.D., 2015. Agricultural landowners' willingness to participate in a filter strip program for watershed protection. Land Use Pol. 49, 75–85.