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Research article

The role of social and personal norms in biodiversity conservation: A segmentation of Swiss farmers

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ABSTRACT

The agricultural sector is a major contributor to global biodiversity loss. Ecological focus areas (EFAs), such as extensively used meadows, hedges, and buffer strips, are a cornerstone in promoting biodiversity conservation. Previous research highlights social and personal norms as strong predictors of farmers' efforts to conserve biodiversity. Accordingly, we aim to segment Swiss farmers according to their social and personal norms and analyze how these segments differ in terms of pro-environmental behavior. Furthermore, we are interested in whether these segments differ in terms of farmer's self-efficacy, the importance of farm sales and biodiversity payments, farmers' political priorities, and socio-demographic and farm characteristics. For the empirical analyses, we used a unique dataset combining data from a survey of Swiss farmers ($N = 882$) with data on registered EFAs from the Swiss Agricultural Information System. We explored the segments based on responses to four items capturing social and personal norms toward biodiversity conservation using latent class analysis. To estimate the mean differences between segments, we used an analysis of variance and covariance. Our results showed that farmer segments with high social and personal norms implemented more EFAs than those with lower social and personal norms. Moreover, high social and personal norms were associated with enhanced self-efficacy, higher importance of biodiversity payments for farm income, stronger priority for environmental policies, and less intensive agricultural production practices. This study informs policymakers in designing social norm interventions that, for example, include information about society's approval of farmers' biodiversity conservation efforts.

1. Introduction

Currently, human activities are causing a high percentage of biodiversity to become extinct (Cowie et al., 2022). The agricultural sector plays a major role in global anthropogenic biodiversity loss (Jaureguiberry et al., 2022; Diop et al., 2024) through land use change (Winkler et al., 2021), over-exploitation of natural resources such as ground water aquifers (Rupérez-Moreno et al., 2017), greenhouse gas emissions from livestock farming (Mohammed et al., 2020), and pesticide pollution (Sun et al., 2018). Biodiversity conservation should be considered a public good that is potentially facing under-provision (Perrings and Gadgil, 2003; Baumgärtner, 2007). Therefore, in the European Union (EU) and Switzerland, agricultural policies provide monetary incentives through direct payments to encourage farmers to provide environmental public goods (Huber et al., 2024). Ecological focus areas (EFAs), such as extensively used meadows and pastures, hedges, traditional orchards, and buffer strips, are a cornerstone in agri-environmental schemes[1] promoting biodiversity conservation on agricultural land (Cullen et al., 2021; Wool et al., 2023; Jan et al., 2024; Zimmert et al., 2024).

The interplay between what peers expect of an individual (i.e., social norms) and the moral standards of the individual themselves (i.e., the personal norm) is crucial in predicting pro-environmental behavior (Cialdini et al., 1990). Accordingly, previous empirical research clearly indicates that social norms and personal norms play an important role in biodiversity conservation in large-scale productive landscapes, such as forests and agricultural areas (Primmer and Karppinen, 2010; Moon et al., 2012; Johansson et al., 2013; Wauters et al., 2017). However,

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[1] Similar to the EU, Swiss voluntary agri-environmental schemes cover a broad range of pro-environmental farming practices (Opdenbosch et al., 2024). In Switzerland, farmers receive direct payments to encourage voluntary participation in activities such as biodiversity conservation through EFA, preventing bush encroachment and forestation of landscapes, avoidance of pesticides in arable farming, careful tillage, and efficient nitrogen application (FOAG, 2023).

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social and personal norms among farmers can be heterogeneous and can influence farmers' pro-environmental behavior differently. To design effective agricultural policies that support on-farm biodiversity conservation, policymakers need more knowledge about how social and personal norms for biodiversity conservation are manifested across the farming population and how farmers with higher norms differ from their peers with lower norms for biodiversity conservation.

The aim of our study is twofold. First, we aim to segment Swiss farmers according to their social and personal norms regarding on-farm biodiversity conservation. Second, we aim to analyze whether these segments differ in terms of implementing EFAs. To gain further insight into the characteristics of different segments of farmers, we examine other variables. Accordingly, we investigate whether segments of farmers differ in terms of farmer's self-efficacy (i.e., the confidence in one's own abilities in a certain domain), the importance of farm sales and biodiversity payments, farmers' political priorities, socio-demographic, and farm characteristics.

For the empirical analyses, we construct a unique dataset combining data from a survey among Swiss farmers ($N = 882$) conducted in 2023 with data on registered EFAs and farm characteristics from the Swiss Agricultural Information System (AGIS). We segment farmers based on their responses to four items capturing social and personal norms regarding on-farm biodiversity conservation using latent class analysis. We use the information of segment membership to test for mean value differences regarding (i) the implementation of EFAs, (ii) farmer's self-efficacy in biodiversity conservation, (iii) the importance of different income sources for total farm income, (iv) farmer's political priorities, (v) socio-demographic characteristics of the farm manager, and (vi) farm characteristics. To estimate the mean value differences between farmer segments, we use a bootstrap-based non-parametric analysis of variance and covariance (ANOVA).

Empirical studies that consider social or personal norms as predictors of EFA implementation typically use econometric techniques, such as linear regression or structural equation modeling, which estimate the average effect of the total population (Mettepenningen et al., 2013; Menozzi et al., 2015; Beer and Theuvsen, 2018; Špur et al., 2018; Otter and Beer, 2021). Thus, these analyses treat farmers as a homogenous group in terms of their personal and social norms, likely masking different norm patterns. Furthermore, previous empirical studies do not jointly consider personal and social norms, whereas we segment farmers based on their personal and social norms regarding biodiversity conservation. Accordingly, to the best of our knowledge, this is the first study to segment farmers based on their social and personal norms regarding on-farm biodiversity conservation. Using this approach allows us to explore the heterogeneity regarding social and personal norms in on-farm biodiversity conservation. Furthermore, we examine whether there are differences in the implementation of EFAs across farmer segments and differences in farmer's self-efficacy or farmer's policy priorities.

The paper is structured as follows. In Section 2, we present the theoretical background and research approach of our study. In Section 3, we describe the databases, variables, measures, and methods used. In Section 4, we present the results, and we discuss them in Section 5. We conclude the article in Section 6.

2. Theoretical background and research approach

Social and personal norms are central elements in a number of theoretical models explaining (pro-environmental) behavior. Well-known examples are the Theory of Reasoned Action (Fishbein and Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991), the Norm Activation Model (Schwartz, 1977), and the Model of Pro-Environmental Behavior (Kollmuss and Agyeman, 2002). According to Burke and Young (2011), social norms can be defined "[…] as a standard, customary, or ideal form of behavior to which individuals in a social group try to conform." Social norms are further divided into injunctive and descriptive norms. Injunctive social norms capture the perceptions of an individual regarding what relevant peers (e.g., the family or close friends of a farmer) approve or think the individual should do (White et al., 2011). Descriptive social norms refer to the perceptions of peers' engagement in a common normative behavior (i.e., in our case, other personally known farmers implement measures that enhance on-farm biodiversity conservation) (Heinicke et al., 2022). By contrast, personal norms are self-defined moral standards of one's own behavior regarding doing 'the right thing' (i.e., in our case, a farmer considers it important to enhance on-farm biodiversity conservation) (Schwartz and Howard, 1981; Perugini et al., 2003). In this context, Schwartz (1973) argued that personal norms are internalized social norms that can be triggered by social norm interventions.

A meta-study by Helferich et al. (2023) highlights the importance of the predictive strength of injunctive, descriptive, and personal norms for pro-environmental behavior. In their direct model[2] shown in Fig. 1, descriptive, injunctive, and personal norms are correlated and jointly influence pro-environmental behavior. Accordingly, the direct model highlights the importance of the interplay between descriptive, injunctive, and personal norms in predicting pro-environmental behavior.

Due to the interrelatedness of descriptive, injunctive, and personal norms, we use the direct model shown in Fig. 1 to segment farmers based on their social (i.e., descriptive and injunctive norms) and personal norms. We expect that the segmentation will result in at least one farmer segment exhibiting high social and personal norms in biodiversity conservation and one farmer segment exhibiting low social and personal norms in biodiversity conservation. The information on farmer membership in a segment can then be used to identify differences in pro-environmental behaviors (i.e., the implementation of EFAs). Here, we expect that farmer segments with a high level of social and personal norms will implement more EFAs than those with a low level of social and personal norms (Barnes et al., 2022; Upadhaya et al., 2023). To further describe the different segments of farmers, we use other variables related to farmers' self-efficacy to conserve biodiversity, the importance of farm sales and biodiversity payments to farm income, farmers' policy priorities, socio-demographic characteristics, and farm characteristics.

3. Data and methods

3.1. Databases, measures, and variables used for the empirical analysis

For our empirical analyses, we combined survey data with data from Swiss AGIS. The two databases are described in Section 3.1.1. The measures and variables used for the empirical analyses are presented in Section 3.1.2.

3.1.1. Databases

The survey was conducted between June and August 2023 among 2000 randomly selected Swiss farmers from the German- and French-speaking regions of the country. We used stratified sampling by agricultural zone and type of farm. Farmers' contact details were provided by the Swiss Federal Office for Agriculture (FOAG), which maintains a database with approximately 48,000 farms receiving direct payments, accounting for over 99% of all Swiss farms. We sent a paper-and-pencil survey to the farmers through postal mail. The letter contained a link through which farmers could alternatively fill out the survey online. We asked farmers about their political priorities, the importance of different sources of farm income, social-psychological aspects, including norms and self-efficacy, and sociodemographic characteristics. The response rate of the survey was 44% ($N = 882$). We combined the survey data

[2] In the mediated model, the effect of norms on pro-environmental behavior are mediated by intentions. We do not consider this model because we do not observe the intention to perform a pro-environmental behavior.

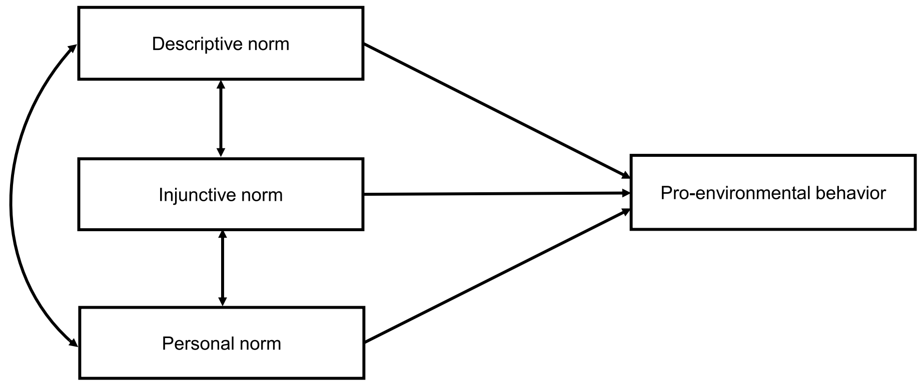

Fig. 1. The direct model (Helferich et al., 2023).

with data from the Swiss AGIS from 2023 (FOAG, 2020) on registered EFAs and farm characteristics, such as utilized agricultural area (UAA), livestock units, farm type, and agricultural zones. Overall, our sample represents the population of Swiss farms well (see Figure A1 in Appendix A).

3.1.2. Measures and variables used for the empirical analyses

Farmers' social and personal norms were measured with norm items adopted from Cialdini et al. (1990) on a 7-point Likert scale. One item refers to the descriptive norm, two items cover injunctive norms, and one item depicts the farmer's personal norm (Table 1). In this study, we considered farmers' registered EFAs as a proxy for their pro-environmental behavior. In Switzerland, the following three types of biodiversity-related EFA exist (see Mack et al., 2020; Huber et al., 2021; Wuepper and Huber, 2022). First, action-oriented EFAs require farmers to fulfill management obligations (e.g., no fertilization of extensive grassland) in order to receive action-oriented payments. Under the cross-compliance scheme,[3] farmers have to implement at least 7% (or 3.5% for special crops, such as vine grapes, berries, fruits, and vegetables) of the UAA as action-oriented EFAs. Second, in addition to the action-oriented EFA, the farmers receive result-oriented payments for the occurrence of targeted indicator species (i.e., rare, endangered plant or animal species) on EFAs. Therefore, we refer to the EFA that is eligible for such payments as the result-oriented EFA. Third, farmers receive additional payments (i.e., agglomeration payments) if the EFA is spatially connected. We therefore call this area spatially connected EFA.

Agglomeration projects are planned and implemented in a bottom-up process involving farmers and local/cantonal authorities. Action- and result-oriented EFAs, local trees, and avenues, as well as region-specific EFAs, can be implemented in agglomeration projects. Compared to action-oriented EFAs, result-oriented EFAs represent a higher quality of biodiversity impact (Meier et al., 2021, 2024a, 2024b; Riedel et al., 2019), and agglomeration EFAs enhance the spatial connectivity of EFAs, which is crucial for reaching biodiversity outcomes (Meier et al., 2024b).

Following Mack et al. (2020), we calculated the following three EFA shares based on data on registered EFAs (in ha) and UAA (in ha):

$$Share\ 1 = \left(\sum Action\text{-}oriented\ EFAs_i \Big/ UAA_i\right) \times 100$$

$$Share\ 2 = \left(\sum Result\text{-}oriented\ EFAs_i \Big/ \sum Action\text{-}oriented\ EFAs_i\right) \times 100$$

$$Share\ 3 = \left(\sum Agglomeration\ EFAs_i \Big/ \sum Action\text{-}oriented\ EFAs_i\right) \times 100$$

where subscript i refers to an individual farm. The first share was calculated by dividing the sum of the action-oriented EFAs by the total UAA. The second and third shares were computed by dividing the sum of the result-oriented EFAs or the sum of the agglomeration EFAs, respectively, by the sum of the action-oriented EFAs. The second and third shares measure the extent to which action-oriented EFAs additionally provide a higher quality of biodiversity and enhanced spatial connectivity in the EFAs. In addition, we used the absolute values of the EFAs (i.e., the size in ha) to check the robustness of our results. The summary statistics of EFA shares and EFA sizes are presented in Table 2.

Furthermore, we used variables related to (i) farmer's self-efficacy according to Bandura (1977), (ii) farmer's ratings on the importance of different farm income sources, (iii) farmer's ratings of different policies (i.e., policy priorities), (iv) farmer's socio-demographic characteristics, and (v) farm characteristics (Table 3). The nominal scaled variables education and agricultural zone are transformed into binary variables. Based on a binary variable, we can calculate the share per farmer segment.

3.2. Methods

We used latent class analysis (LCA) to segment Swiss farmers in terms of their social and personal norms in on-farm biodiversity conservation. LCA is a probabilistic modeling technique used to identify segments or subgroups of individuals within a population. These "hidden" segments are referred to as latent classes or segments (Weller et al., 2020; Sinha et al., 2021). This implies that there is no variable in the dataset indicating the membership of an individual within a latent segment. To reveal latent segments, individuals' responses to a set of observed nominal, ordinal, or continuous variables are the basis (Porcu and Giambona, 2017). This segmentation technique is considered an alternative to stratification; therefore, individuals are classified into segments based on the patterns of responses (Mundal et al., 2021). Thus, LCA is considered a person-centered method, allowing for modeling heterogeneity regarding social and personal norms in the realm of biodiversity conservation within the population. By contrast, findings from variable-oriented methods, such as linear regression, capture information about relationships between the variables of interest for the overall population (Scotto Rosato and Baer, 2012). To model heterogeneity in LCA, the latent variable is drawn from a population of S latent segments (whereby $s = 1, \ldots, S$ segments) (Brown et al., 2014). The membership in a segment of farmer i, the number of latent segments S, and their frequency within the total population are unknown in

[3] Similar to the EU, Swiss farmers have to fulfill the cross-compliance standard to be eligible receiving direct payments. In addition to the implementation of action-oriented EFAs, the cross-compliance scheme inter alia covers the following requirements: 1) Keeping farm animals in accordance with animal welfare the legislation, 2) balanced use of fertilizers, 3) strict crop rotation, 4) appropriate soil protection measures, and 5) appropriate selection and application of plant protection products (FOAG, 2024).

Table 1
Summary statistics of the norm items.

Variable description	Scale	Mean	Std. dev.	Min.	Max.	Obs.	Source
Social and personal norms used for the latent class analysis: To what extent do the following statements about enhancing biodiversity apply to you?							
Descriptive norm – other farmers: "Most of the farmers I personally know take measures to promote biodiversity on their farms."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	4.4	1.7	1	7	866	Survey
Injunctive norm – family: "My family members expect me to take measures to promote biodiversity on my farm."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	3.5	2.0	1	7	867	Survey
Injunctive norm – acquaintances: "Most of my acquaintances expect me to take measures to promote biodiversity on my farm."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	3.4	1.8	1	7	865	Survey
Personal norm: "I think it is important to take measures to promote biodiversity on my farm."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	4.8	1.8	1	7	868	Survey

Table 2
Summary statistics of the EFA shares 1–3 and EFA sizes 1–3.

Variable description	Scale	Mean	Std. dev.	Min.	Max.	Obs.	Source
EFA share							
Share 1: (Action-oriented EFAs/UAA)	Share in %	21.8	17.9	2.8	180.1	876	AGIS
Share 2: (Result-oriented EFAs/Action-oriented EFAs)	Share in %	39.6	31.0	0.0	100.0	876	AGIS
Share 3: (Agglomeration EFAs/Action-oriented EFAs)	Share in %	77.0	35.0	0.0	159.9	876	AGIS
EFA size							
Size 1: Action-oriented EFAs	Continuous in ha	5.0	6.0	0.1	81.4	876	AGIS
Size 2: Result-oriented EFAs	Continuous in ha	2.2	4.0	0.0	57.1	876	AGIS
Size 3: Agglomeration EFAs	Continuous in ha	4.1	5.3	0.0	80.5	876	AGIS

advance. Accordingly, LCA is an exploratory method (Oberski, 2016).

Fig. 2 represents an LCA model that depicts observed variables as boxes and latent variables as circles.

A farmers' norm profile in the context of on-farm biodiversity conservation is considered a latent variable, which is constructed based on four 7-point Likert-scaled items (see Table 1). Based on the response patterns, an individual farmer is then assigned to one of the S latent segments. The more similar the response patterns are, the more homogeneous a latent segment (Zhang et al., 2018). Accordingly, LCA can reveal heterogeneity when at least one of the latent segments exhibits a response pattern with high ratings of the observed items and when one latent segment indicates a response pattern with low ratings of the observed items (Nylund-Gibson and Choi, 2018).

To estimate the latent segments, we used the R software package poLCA (Linzer and Lewis, 2011). Class or segment membership probabilities and item-response probabilities were estimated by maximum likelihood using the expectation–maximization algorithm. Class or segment membership probabilities refer to the probability of an individual's segment membership. The item-response probabilities indicate the relationship between the observed variables and the latent segments (Ulbricht et al., 2018). The optimal number of latent segments is determined based on comparative model fit criteria, such as the (adjusted) Bayesian information criterion (aBIC), and the (consistent) Akaike information criterion (cAIC). In principle, a decreasing value of comparative model fit criteria indicates a better model fit (Vrieze, 2012). In this context, Brandenburger and Schwichow (2023) provided some suggestions. When describing heterogeneity as more important than the simplicity of the model or when similar segments that still have distinct differences are assumed, AIC or aBIC should be chosen than BIC or cAIC. To obtain fewer but larger segments, and if AIC reveals a high number of segments that are hard to interpret, BIC is more suitable. Additionally, the theoretical interpretability and usefulness of the identified model should be considered when choosing a solution (Rost, 2004; Weller et al., 2020).

To calculate the mean value differences between latent segments for EFA shares, EFA sizes, and further variables of interest, we used ANOVA. ANOVA assesses the relative value of variance among segment means (i.e., the between-segment variance) compared to the average variance within segments (i.e., the within-segment variance) (Kim, 2014). To handle potential non-normality and heteroscedasticity (non-equal variances) of residuals, we applied a bootstrap-based non-parametric ANOVA (Zhou and Wong, 2011).

4. Results

4.1. Farmer segments based on their social and personal norms for biodiversity conservation

Table 4 presents the comparative model fit criteria (AIC, cAIC, BIC, and aBIC) of the LCA. For all comparative model fit criteria, we observed the largest decrease in comparative fit values between $S = 2$ and $S = 3$. Furthermore, the values of the AIC and the aBIC constantly decreased across the number of latent segments, whereas the values of the cAIC and the BIC pointed to $S = 3$ as the optimal segment solution. To avoid segment solutions that were difficult to interpret, we chose $S = 3$ as the optimal segment solution.

Fig. 3 is a visualization of the farmer's response patterns for the items capturing (a) descriptive norm, (b) injunctive norm – family, (c) injunctive norm – acquaintances, and (d) personal norm based on the segment solution $S = 3$. The relative frequency of responses ranging from 1 = strongly disagree (color dark orange) to 7 = strongly agree (color lavender) is depicted on the left axis, while the share of a farmer segment within the total population is shown on the top axis. The labeling and separation of the segments should be meaningful (Sinha et al., 2021). Accordingly, we labeled each of the three segments according to their response patterns on the bottom axis. However, owing to the complexity of the segments, a labeling fallacy can occur, implying that the segment label may not accurately reflect segment membership (Weller et al., 2020). In other words, perfect homogeneity within segments and perfect heterogeneity between segments are unlikely. Rather, the higher the number of segments, the higher the likelihood of heterogeneity within segments and homogeneity between segments. Thus, we are confident that homogeneity within segments and heterogeneity between segments are best achieved by choosing $S = 3$ as the optimal solution. As a robustness check, in subsection 4.3, we present the results of the LCA and the results of the ANOVA for differences in the implementation of EFAs based on segment solution $S = 4$.

The first farmer segment, which we labeled "low biodiversity norms," represented 30.6% (n = 264) of the total population. In particular, for the items capturing the expectations of family members

Table 3
Summary statistics of the other variables used.

Variable description	Scale	Mean	Std. dev.	Min.	Max.	Obs.	Source
Self-efficacy: Please indicate the extent to which the following statements about your skills and knowledge in the field of improving biodiversity apply to you.							
Self-efficacy – personal skills: "I possess the necessary skills and knowledge to enhance biodiversity on my farm."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	5.2	1.5	1.0	7.0	867	Survey
Self-efficacy – damage prevention: "I am confident that I can prevent damage to biodiversity caused by agricultural production."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	5.4	1.5	1	7	861	Survey
Self-efficacy – overcoming difficulties: "If difficulties arise when implementing measures to enhance biodiversity, I usually find a solution."	Likert scale from 1 = Strongly disagree to 7 = Strongly agree	5.3	1.4	1	7	862	Survey
Importance of farm income sources: Please indicate the importance of each source of income for your farm income.							
Farm sales	Likert scale from 1 = Not important at all to 7 = Very important	5.9	1.5	1	7	859	Survey
Biodiversity direct payments	Likert scale from 1 = Not important at all to 7 = Very important	5.1	1.9	1	7	865	Survey
Policy priority: For the following aspects, please indicate how important they should be in the distribution of the agricultural budget (or direct payments).							
Promote biodiversity	Likert scale from 1 = Not important at all to 7 = Very important	4.6	1.6	1	7	863	Survey
Promote animal welfare	Likert scale from 1 = Not important at all » to 7 = Very important	4.6	1.7	1	7	862	Survey
Reduce consumer prices	Likert scale from 1 = Not important at all » to 7 = Very important	2.7	1.8	1	7	858	Survey
Ensure appropriate farm income	Likert scale from 1 = Not important at all » to 7 = Very important	6.3	1.1	1	7	863	Survey
Increase domestic food production	Likert scale from 1 = Not important at all » to 7 = Very important	6.0	1.3	1	7	861	Survey
Reduce greenhouse gas emissions	Likert scale from 1 = Not important at all » to 7 = Very important	4.0	1.7	1	7	861	Survey
Reduce nutrient surplus	Likert scale from 1 = Not important at all » to 7 = Very important	4.4	1.7	1	7	861	Survey
Reduce pesticide application	Likert scale from 1 = Not important at all » to 7 = Very important	4.5	1.7	1	7	865	Survey
Farmer's socio-demographic characteristics							
Gender	Binary 1 = males; 0 = females	0.9	0.3	0.0	1.0	873	Survey
Age farm manager	Continuous in years	50.0	10.1	22.0	66.0	882	AGIS
Full- or part-time farming	Binary 1 = full-time; 0 = part-time	0.8	0.4	0.0	1.0	875	Survey
Language region	Binary 1 = German-speaking; 0 = French-speaking	0.8	0.4	0.0	1.0	882	Survey
Education							
Practical experience	Binary 1 = yes; 0 = no	0.1	0.2	0.0	1.0	863	Survey
Apprenticeship	Binary 1 = yes; 0 = no	0.0	0.1	0.0	1.0	863	Survey
Federal vocational certificate	Binary 1 = yes; 0 = no	0.1	0.2	0.0	1.0	863	Survey
Federal certificate of competence	Binary 1 = yes; 0 = no	0.4	0.5	0.0	1.0	863	Survey
Professional experience	Binary 1 = yes; 0 = no	0.1	0.3	0.0	1.0	863	Survey
Master's examination	Binary 1 = yes; 0 = no	0.2	0.4	0.0	1.0	863	Survey
Higher college	Binary 1 = yes; 0 = no	0.0	0.2	0.0	1.0	863	Survey
University	Binary 1 = yes; 0 = no	0.1	0.2	0.0	1.0	863	Survey
Other	Binary 1 = yes; 0 = no	0.0	0.2	0.0	1.0	863	Survey
Farm characteristics							
UAA	Continuous in hectare	23.2	15.1	0.3	112.8	882	AGIS
Livestock units per hectare	Continuous units per hectare	1.2	0.9	0.0	7.5	882	AGIS
Organic farms	Binary 1 = organic; 0 = conventional	0.2	0.4	0.0	1.0	882	AGIS
Agricultural zone							
Valley Zone	Binary 1 = yes; 0 = no	0.4	0.5	0.0	1.0	882	AGIS
Hill zone	Binary 1 = yes; 0 = no	0.2	0.4	0.0	1.0	882	AGIS
Mountain zone I	Binary 1 = yes; 0 = no	0.1	0.3	0.0	1.0	882	AGIS
Mountain zone II	Binary 1 = yes; 0 = no	0.2	0.4	0.0	1.0	882	AGIS
Mountain zone III	Binary 1 = yes; 0 = no	0.1	0.3	0.0	1.0	882	AGIS
Mountain zone IV	Binary 1 = yes; 0 = no	0.0	0.2	0.0	1.0	882	AGIS

and friends to promote on-farm biodiversity (i.e., injunctive norm – family and injunctive norm – acquaintances), farmers mostly indicated the lowest value of 1 (injunctive norm – family = 68.2%; injunctive norm – acquaintances = 60.6%) or 2 (injunctive norm – family = 30.0%; injunctive norm – acquaintances = 33.0%). Thus, pro-environmental behavior in this farmer segment was not influenced by the expectations of family members or friends. Compared to injunctive norms, the response patterns for personal and descriptive norms were more heterogeneous. Nevertheless, more than 50% of the responses for these items scored low values of 1, 2, or 3 (descriptive norm = 55.7%; personal norm = 52.7%).

We labeled the second farmer segment "medium biodiversity norms." This segment represents 30.7% (n = 265) of the total population. Three quarters of the responses for the items injunctive norms – family and injunctive norm – acquaintances were at the low or medium values of 3 (injunctive norm – family = 38.5%; injunctive norm – acquaintances = 40.4%) and 4 (injunctive norm – family = 37.4%; injunctive norm – acquaintances = 37.4%). Thus, farmers belonging to this segment were indifferent about whether the expectations of family members and friends could influence the decision to promote on-farm biodiversity. Similarly, a large proportion of about 50% of the responses for the items descriptive and personal norms were at the low value of 3 (descriptive norm = 17.0%; personal norm = 16.2%) and the medium value of 4 (descriptive norm = 37.0%; personal norm = 33.6%). However, compared to the segment "low biodiversity norms," farmers belonging to the segment "medium biodiversity norms" more frequently indicated higher values of 5, 6, and 7. For example, for the item personal norm, 26.4% of farmers indicated a value of 5, 11.3% indicated a value

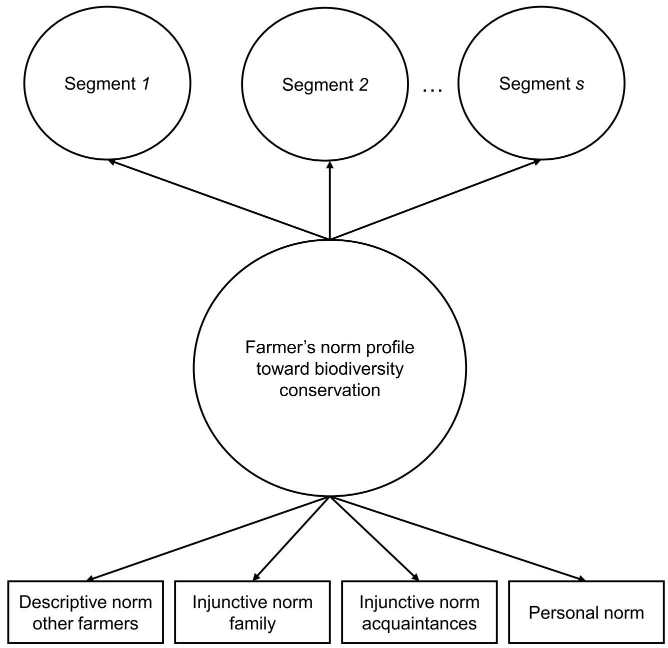

Fig. 2. Representation of an LCA model (Naldi and Cazzaniga, 2020).

Table 4
Comparative model fit criteria of the latent class analysis.

Number of latent segments *S*	AIC	cAIC	BIC	aBIC
2	11,929	12,211	12,162	12,007
3	11,640	12,066	11,992	11,757
4	11,499	12,069	11,970	11,656
5	11,380	12,094	11,970	11,577

of 6, and 10.9% indicated a value of 7.

With a share of 38.7% (n = 334), the segment "high biodiversity norms" was the largest within the total population. For the item personal norm, farmers belonging to this segment almost exclusively indicated high values of 5 (26.4%), 6 (26.4%), and 7 (45.2%). Similarly, the farmers indicated a high level of agreement for the items injunctive norm – family (5 = 38.2%, 6 = 22.5%, 7 = 23.1%), injunctive norm – acquaintances (5 = 37.4%, 6 = 18.0%, 7 = 13.5%), and descriptive norm (5 = 31.4%, 6 = 18.3%, 7 = 19.8%). Consequently, the decisions of farmers belonging to this segment are likely driven by high personal norms, high expectations of family members and friends, and by the decisions of other known farmers.

4.2. Differences between farmer segments in terms of pro-environmental behavior

The differences in the implementation of EFAs between the three farmer segments using the confidence interval plots are shown in Fig. 4. Mean values are shown by point symbols, and the 90% confidence intervals are shown by capped bars. The three plots at the top of Fig. 4 represent EFA shares 1–3, and the three plots at the bottom represent EFA sizes 1–3. As overlapping confidence intervals do not necessarily indicate a statistically non-significant difference in mean values between segments (Greenland et al., 2016), we further present the results of the ANOVA in Table 5. The mean values used in the ANOVA are shown in Table B1 in Appendix B.

The ANOVA results showed that farmers belonging to the "high biodiversity norms" segment had, on average, 8.0 percentage points higher shares of action-oriented EFAs than farmers belonging to the "low biodiversity norms" segment. Compared to farmers in the "medium biodiversity norms" segment, farmers in the "high biodiversity norms" segment had, on average, 6.4 percentage points higher shares of action-oriented EFAs. Farmers in the medium- and high-norm segments had a significantly higher share of result-oriented EFAs than farmers in the

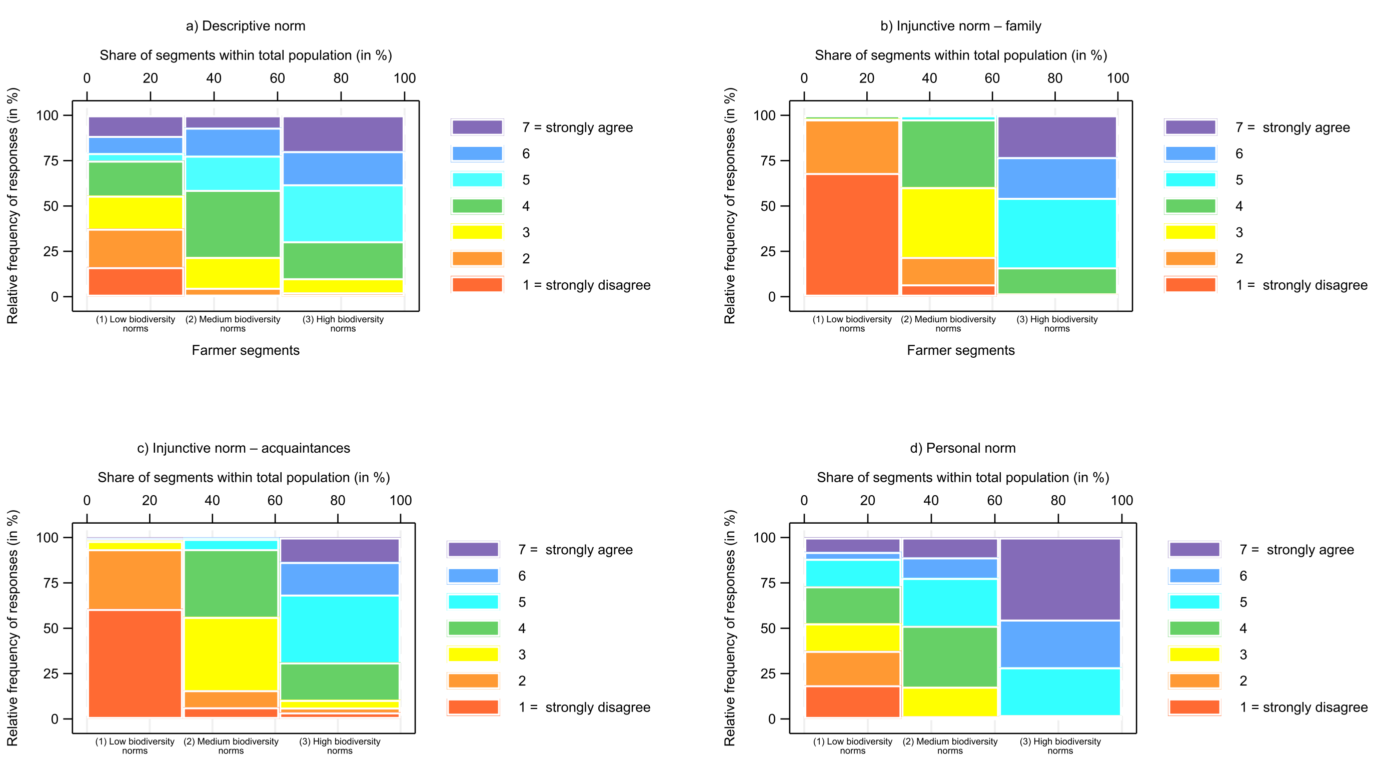

Fig. 3. Farmer's response patterns for the items a) descriptive norm, b) injunctive norm – family, c) injunctive norm – acquaintances, and d) personal norm based on segment solution $S = 3$.

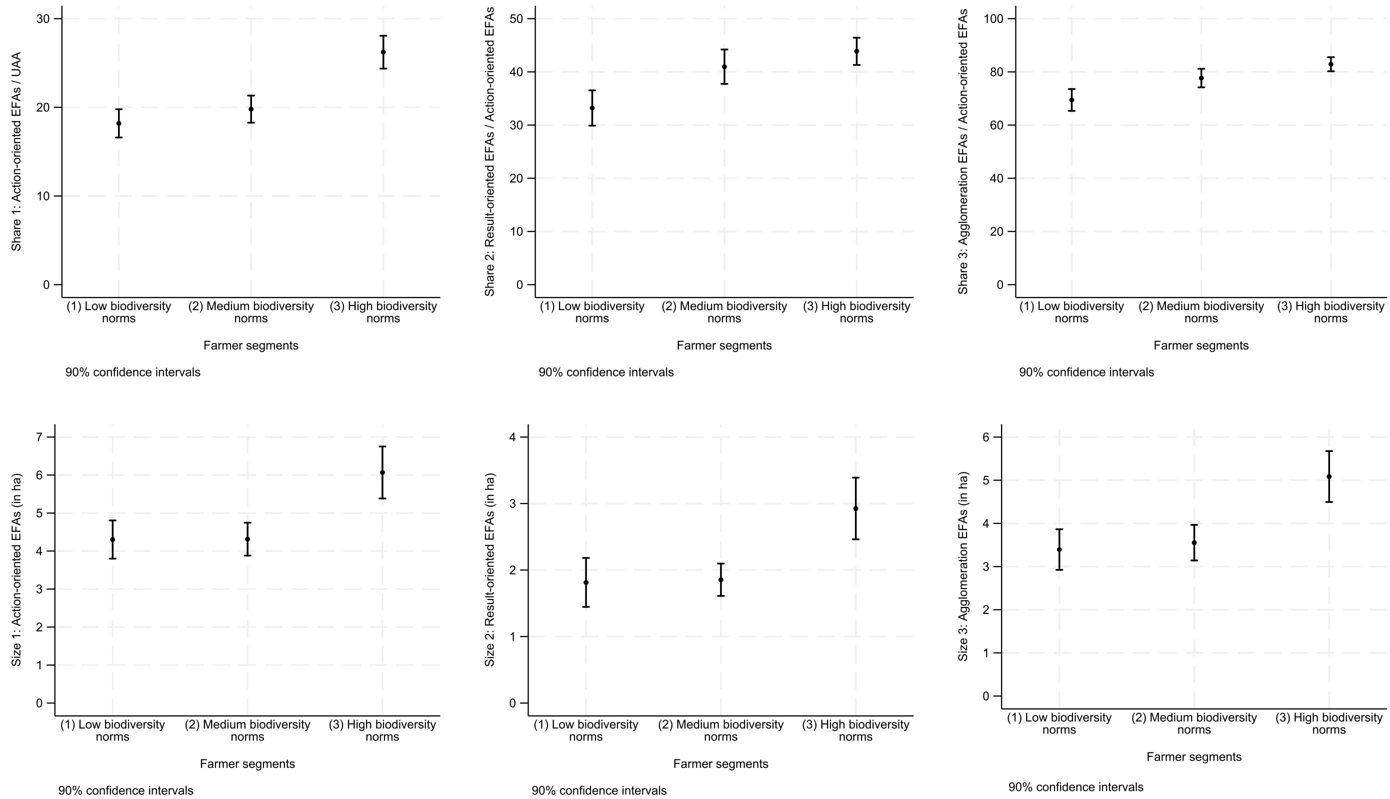

Fig. 4. Confidence interval plots visualizing the differences in the implementation of EFAs between the three farmer segments.

Table 5
Results of the ANOVA for EFA shares and EFA sizes.

Variable	Mean difference low norms – medium norms	Mean difference low norms – high norms	Mean difference medium norms –high norms
EFA share			
Share 1: (Action-oriented EFAs/UAA)	−1.6	−8.0***	−6.4***
Share 2: (Result-oriented EFAs/ Action-oriented EFAs)	−7.8***	−10.7***	−2.9
Share 3: (Agglomeration EFAs/Action-oriented EFAs)	−8.2***	−13.4***	−5.2**
EFA size			
Size 1: Action-oriented EFAs	0.0	−1.8***	−1.8***
Size 2: Result-oriented EFAs	−0.1	−1.1***	−1.0***
Size 3: Agglomeration EFAs	−0.2	−1.7***	−1.5***

***, **, and * denote significance at 1%, 5%, and 10% respectively.

low-biodiversity norm segment. Farmers belonging to the high-biodiversity norm segment implemented a higher share of agglomeration EFAs than farmers belonging to the low- and medium-norm segments. For example, the average difference between the high-biodiversity norm segment and the low-biodiversity norm segment amounted to 13.4 percentage points. With regard to the size of the EFAs, we generally observed no statistically significant mean value difference between farmers with low biodiversity norms and farmers with medium biodiversity norms. By contrast, farmers with high biodiversity norms consistently had significantly more EFA than farmers with low and medium biodiversity norms.

4.3. Mean differences for variables characterizing farmer segments

The results of the ANOVA based on variables referring to farmers' self-efficacy, importance of farm sales, and biodiversity payments for farm income and policy priorities are presented in Table 6. The mean values used in the ANOVA are shown in Table B2 in Appendix B.

Findings from the ANOVA showed that farmers belonging to the "low biodiversity norms" segment and the "medium biodiversity norms" segment had similar levels of self-efficacy for biodiversity conservation. By contrast, compared to farmers in the "low biodiversity norms" segment and in the "medium biodiversity norms" segments, farmers belonging to the "high biodiversity norms" segment consistently had significantly higher self-efficacy. For example, farmers with high biodiversity norms rated their personal skills for biodiversity conservation 0.9 points higher than farmers with low biodiversity norms and 0.7 points higher than farmers with medium biodiversity norms.

All farmer segments considered farm sales to be an important source of farm income. For biodiversity payments, we found a statistically significant higher importance for farmers in the medium and high-biodiversity norm segments compared to farmers in the low-biodiversity norm segment, and a statistically significant higher importance for farmers in the high-biodiversity norm segment compared to farmers in the medium-biodiversity norm segment.

Regarding the policy priorities, we found a statistically significant higher priority of promoting biodiversity for farmers in the medium- and high-diversity norm segments compared to farmers in the low-norm segment. Furthermore, a statistically significant higher importance of promoting biodiversity was observed for farmers in the high-norm segment compared to farmers in the medium-norm segment. Similar results were observed for other policy priorities related to the protection of the environment (i.e., reducing greenhouse gas emissions, nutrient surplus, and pesticide application) and for the promotion of animal welfare. Compared to farmers in the low-norm segment, reducing consumer prices was slightly more important for the farmers in the medium-

Table 6
Results of the ANOVA for variables related to self-efficacy, importance of farm sales and biodiversity payments for farm income, and policy priorities.

Variable	Mean difference low norms – medium norms	Mean difference low norms – high norms	Mean difference medium norms –high norms
Self-efficacy			
Personal skills biodiversity conservation	−0.2	−0.9***	−0.7***
Damage prevention biodiversity	−0.2	−0.7***	−0.5***
Find solutions for difficulties biodiversity conservation	−0.1	−0.7***	−0.6***
Importance of farm income sources			
Farm sales	+0.2	+0.1	−0.1
Biodiversity payments	−0.7***	−1.4***	−0.7***
Policy priority			
Promote biodiversity	−0.9***	−1.7***	−0.8***
Promote animal welfare	−0.4**	−0.7***	−0.3***
Reduce consumer prices	−0.3**	−0.3*	0.0
Ensure appropriate farm income	0.0	0.0	0.0
Increase domestic food production	+0.1**	+0.5***	+0.4***
Reduce greenhouse gas emissions	−0.7***	−1.3***	−0.6***
Reduce nutrient surplus	−0.6***	−1.2***	−0.6***
Reduce pesticide application	−0.8***	−1.2***	−0.5***

***, **, and * denote significance at 1%, 5%, and 10% respectively.

and high-norm segments, whereas we found no difference in mean values between farmers in the medium- and high-norm segments. For all farmer segments, ensuring an appropriate farm income was of equal importance. Increasing domestic food production as a policy priority was more important for farmers in the segments with low and medium biodiversity norms compared to farmers in the segment with high biodiversity norms. The results also revealed that increasing domestic food production was more important for farmers in the segment with low biodiversity norms than for farmers in the segment with medium biodiversity norms.

The results of the ANOVA based on variables referring to farmers' socio-demographic characteristics and farm characteristics are presented in Table 7. The mean values used in the ANOVA are shown in Table B2 in Appendix B.

For most of the socio-demographic characteristics, we did not observe differences between the three segments. Only for the variable education did we identify a few statistically significant differences between the segments. The share of farmers with higher college education was 2.6 percentage points higher in the high-norm segment than in the low- and medium-norm segments, and the share of farmers with a university degree was 3.6 percentage points higher than in the low-norm segment.

The number of livestock units per hectare was, on average, 0.3 units statistically significantly higher when comparing farmers in the low- and high-norm segments and, on average, 0.2 units higher when comparing farmers in the medium- and high-norm segments. The share of organic farmers in the high-norm segment was 14.9 percentage points higher compared to farmers in the low-norm segment and 11.6 percentage points higher compared to farmers in the medium-norm segment. The share of farms located in mountain zone IV was statistically significantly higher in the high-norm segment compared to the low- and medium-norm segments.

Table 7
Results of the ANOVA for variables related to farmers' sociodemographic characteristics and farm characteristics.

Variable	Mean difference low norms – medium norms	Mean difference low norms – high norms	Mean difference medium norms –high norms
Socio-demographic characteristics			
Share males	−2.7	+0.9	+3.6
Age farm manager	0.0	+0.2	+0.2
Share full-time farms	+4.6	+4.0	−0.6
Share farms German-speaking region	+3.0	+3.0	0.0
Education			
Share practical experience	−0.4	+0.2	+0.6
Share apprenticeship	+0.4	+0.1	−0.3
Share federal vocational certificate	−1.1	+1.0	+2.1
Share federal certificate of competence	−1.8	+2.2	+4.3
Share professional experience	+5.1*	+5.0	0.0
Share master's examination	−2.4	−4.6	−2.1
Share higher college	0.0	−2.6*	−2.6*
Share university	−1.8	−3.6**	−1.8
Share other	+2.0	+1.9	−0.1
Farm characteristics			
UAA	+1.7	+0.4	−1.3
Livestock units per hectare	+0.1	+0.3***	+0.2***
Share organic farms	−3.3	−14.9***	−11.6***
Agricultural zone			
Share farms in valley zone	+0.7	+1.4	+0.7
Share farms in hill zone	+0.9	+1.8	+0.9
Share farms in mountain zone I	−1.4	−1.2	+0.2
Share farms in mountain zone II	+3.5	+4.0	+0.5
Share farms in mountain zone III	−2.6	−1.9	+0.7
Share farms in mountain zone IV	−1.1	−4.1***	−3.0*

***, **, and * denote significance at 1%, 5%, and 10% respectively.

4.4. Robustness check

The $S = 4$ segment solution revealed a small segment 4 with very high biodiversity norms, which had a share of 13.1% (n = 113) within the total population (see Fig. B1 in Appendix B). The response patterns of farmer segment 4 indicated, to a large extent, high values (i.e., 5, 6, and 7). The third segment, "high biodiversity norms," had a share of 38.0% (n = 328) within the total population and was therefore similar in size to the high-biodiversity norm segment in the case of the $S = 3$ segment solution. The item response patterns of farmer segment 3 mostly showed medium to high values (i.e., 4, 5, 6, and 7). The farmer segments 1 "low biodiversity norms" and 2 "medium biodiversity norms" were smaller than in the case of the $S = 3$ segment solution. Segment 1 had a share of 21.8% (n = 188) of the total population, and segment 2 had a share of 27.1% (n = 234). These segments still mainly showed low to medium biodiversity norms (i.e., values 1, 2, 3, and 4).

For the EFA shares, we observed similar patterns as for the $S = 3$ segment solution (see confidence interval plots Fig. B2, results of the ANOVA Table B3, and mean values used in the ANOVA Table B4 in Appendix B). Higher biodiversity norms were still associated with higher

EFA shares. Only EFA share 2 lacked statistically significant differences between farmer segments 2, 3, and 4. Nevertheless, farmer segments 2, 3, and 4 had higher EFA shares 2 and 3 than farmer segment 1. For the EFA sizes, no statistically significant differences were observed between farmer segments 1, 2, and 3. The only exceptions were EFA sizes 1–3, in which farmer segment 3 had statistically significantly larger EFAs than farmer segment 2. For EFA sizes 1–3, we observed a higher EFA implementation for farmer segment 4 than for farmer segments 1, 2, and 3.

5. Discussion

The results of the LCA revealed three segments of farmers in terms of social and personal norms regarding biodiversity conservation (i.e., segment 1 = low biodiversity norms, segment 2 = medium biodiversity norms, and segment 3 = high biodiversity norms). In all cases, the ANOVA results showed that farmers belonging to segment 3 had higher shares and sizes of the three EFA types. Our results are in line with other studies investigating whether different norm segments are associated with differences in farmers' pro-environmental behavior. Barnes et al. (2022) showed that the 'enabled ecologists' farmer segment is more likely to participate in voluntary agri-environmental schemes than the other three farmer segments (i.e., the constrained ecologists, the balanced ecologists, and the unengaged). Similarly, Upadhaya et al. (2023) revealed that the conservationist farmer type is more engaged in adopting innovative conservation practices than the deliberative, productivist, and traditionalist farmer types. These findings raise the question of how social and personal norms can be activated to support the transition to more biodiversity-friendly farming practices, especially among the segment of farmers with low biodiversity norms. De Groot et al. (2021) suggested the introduction of social norm interventions, focusing on descriptive and injunctive social norms. Such interventions comprise, for example, the provision of information to farmers about the quantity and quality of EFAs implemented by other farmers and information about the extent to which society approves the implementation of EFAs (Howley and Ocean, 2021; Van Valkengoed et al., 2022). The activation of social norms through interventions can, in turn, positively influence farmers' personal norms toward biodiversity conservation.

Farmers belonging to the high-norm segment show higher self-efficacy in terms of personal skills, damage prevention, and finding solutions when difficulties arise in biodiversity conservation than the other two segments of farmers. Therefore, our findings suggest that high biodiversity norms are associated with high self-efficacy, which, in turn, leads to a higher implementation of EFAs. However, research on the correlation between social and personal norms and self-efficacy is scarce. Maran et al. (2023) showed that personal and social norms related to climate change, and climate self-efficacy are positively correlated. Thøgersen (2014) revealed that self-efficacy is a mediator of descriptive norms in predicting pro-environmental behavioral intention. Surprisingly, in agricultural sociology and economics, self-efficacy as a predictor of on-farm biodiversity conservation seems to be widely neglected. According to Upadhaya et al.'s (2023) study, the conservationist farmer type has a high conservation self-efficacy, and McGinty et al. (2008) showed that a farmer's self-efficacy has a strong positive effect on the adoption of agroforestry systems.

As the implementation of EFAs can lead to a decrease in agricultural production and an increase in opportunity and/or transaction costs, the economic compensation of EFAs through direct payments is important (Pe'er et al., 2017). For Switzerland, the studies by Karali et al. (2014) and Enri et al. (2020) highlight the beneficial effects of Swiss agricultural direct payments for on-farm biodiversity conservation. Our findings also confirm the important role of biodiversity payments in on-farm biodiversity conservation. In particular, biodiversity payments are more important for the farm incomes of the medium- and high-norm segments than for the low-norm segments. Interestingly, while we mostly observed no differences in the implementation of EFAs between the low- and medium-biodiversity norm segments, in all cases, the high-biodiversity norm segment had a higher implementation of EFAs.

Although the farmer segments with high and medium biodiversity norms showed higher acceptance of environmental and animal welfare policies, these policies appeared to be unpopular among farmers belonging to the low-biodiversity norm segment. Research has shown that personal norms are an important predictor of public support for environmental policies (Nilsson et al., 2004; Harring and Jagers, 2018). Social norms are also particularly important for the acceptance of environmental policies. When only a minority, instead of a majority of the public, supports a policy, its acceptability is often lower (De Grot and Schuitema, 2012).

Compared to farmers in the low- and medium-norm segments, farmers in the high-norm segment have a lower livestock density. Herzog et al. (2006) showed that a higher intensity of agricultural production, measured by livestock density and the number of pesticide applications, is associated with low crop diversity. In Switzerland, 18% of UAA are farmed organically (Bio Suisse, 2024). About a third of the farmers in the high-norm segment are certified organic. The share of organic farmers in the high-norm segment is therefore significantly higher than in the other segments and higher than in Switzerland as a whole. These results are in line with the comparative study by Kings and Ilbery (2010), who showed that compared to conventional farmers, organic farmers have an ecocentric approach to agri-environmental issues with a belief in the need for a biodiverse and sustainable countryside. With regard to differences in on-farm biodiversity conservation between organic and conventional farms, a comparative review by Hole et al. (2005) shows that organic farming practices, such as the prohibition of chemical pesticides and inorganic fertilizers or the extensive management of non-cropped habitats, are more beneficial for biodiversity.

6. Conclusion

To design effective agricultural policies that support on-farm biodiversity conservation, policymakers need more knowledge about the relationships between different norm segments and pro-environmental behavior. Accordingly, the aim of this study was to segment Swiss farmers according to their social and personal norms and to analyze how these segments differ in the implementation of EFAs. Our results clearly show that farmers with higher social and personal norms implemented larger EFAs than farmers with lower biodiversity norms. Moreover, high social and personal norms in biodiversity conservation were associated with enhanced personal self-efficacy, with a higher importance of biodiversity payments for farm income, with a stronger preference for environmental and animal welfare policies, and with less intensive agricultural production practices. We recommend that policymakers focus on activating social norms (i.e., descriptive and injunctive norms) through interventions among farmers with low biodiversity conservation efforts. Such interventions comprise, for example, the provision of information to farmers about the quantity and quality of EFAs implemented by other farmers and information about the extent to which society approves the implementation of EFAs. The activation of social norms through interventions can, in turn, positively influence farmers' personal norms toward biodiversity conservation.

CRediT authorship contribution statement

Christian Ritzel: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Antonia Kaiser:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yanbing Wang:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Gabriele Mack:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Descriptive statistics of sample representativeness

Figure A1 presents comparisons of the sample to the population of all farms in Switzerland in terms of farm type, agricultural zone, and farm size. Overall, the farms in our sample represent the population well. Farms in the valley zone are slightly overrepresented, and farms in mountain zones 3 and 4 are slightly underrepresented (Figure A1(b)).

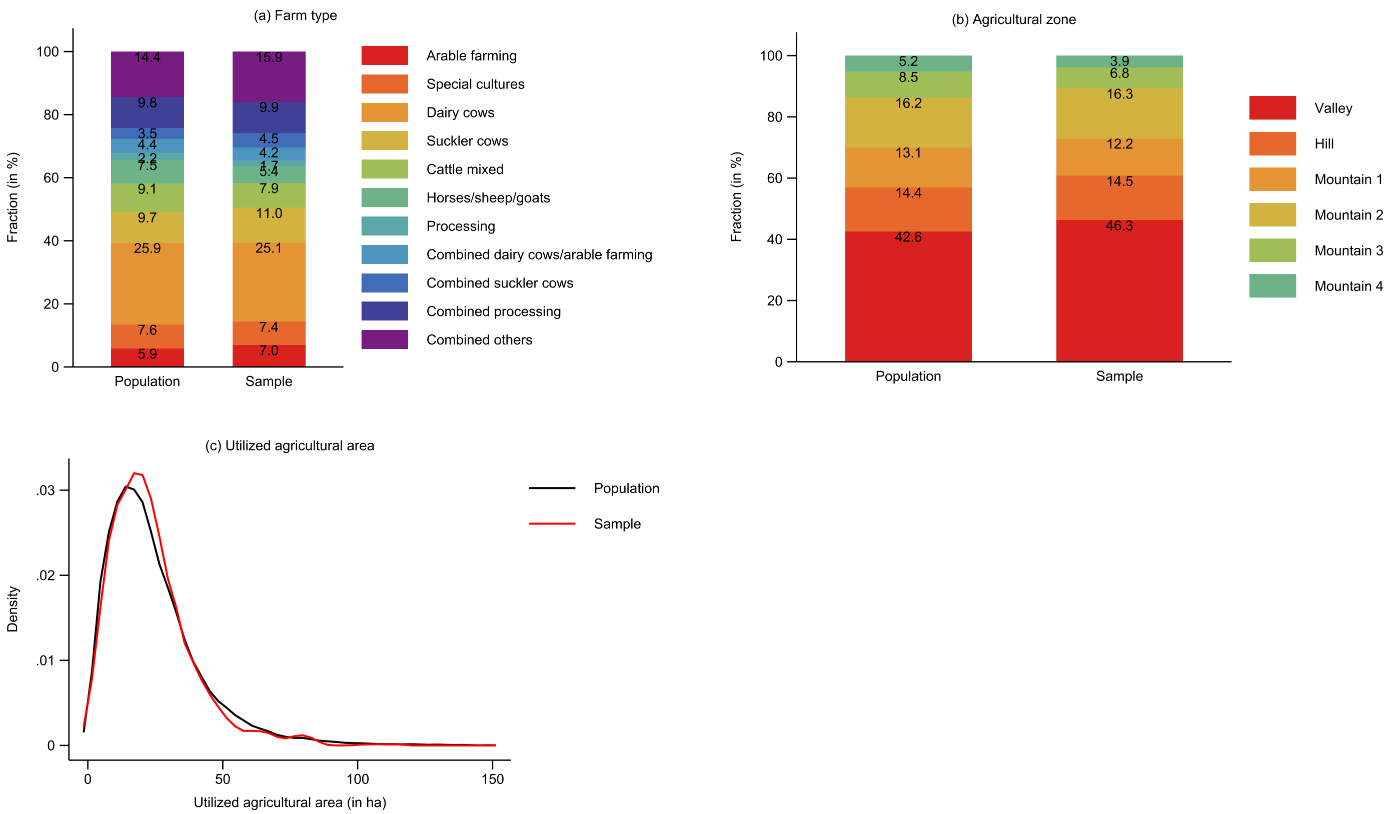

Fig. A1. Representativeness of the sample in terms of farm type, agricultural zone, and utilized agricultural area.

Appendix B

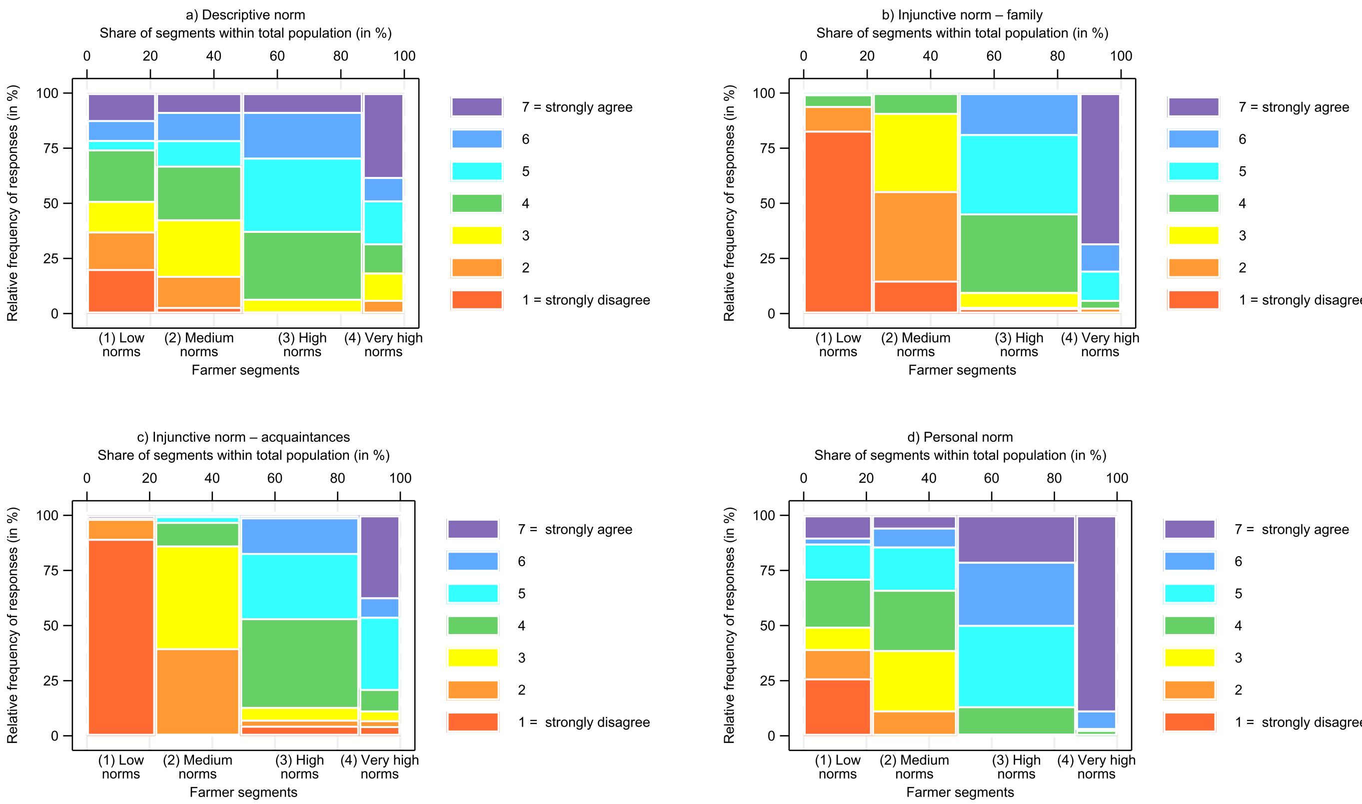

Fig. B1. Farmer's response patterns based on the $S = 4$ segment solution.

Table B1
Mean values used in the ANOVA.

Variable	Mean low norms	Mean medium norms	Mean high norms
EFA share			
Share 1: (Action-oriented EFAs/UAA)	18.2	19.8	26.2
Share 2: (Result-oriented EFAs/Action-oriented EFAs)	33.2	41.0	43.9
Share 3: (Agglomeration EFAs/Action-oriented EFAs)	69.5	77.7	82.9
EFA size			
Size 1: Action-oriented EFAs	4.3	4.3	6.1
Size 2: Result-oriented EFAs	1.8	1.9	2.9
Size 3: Agglomeration EFAs	3.4	3.6	5.1

Table B2
Mean values used in the ANOVA.

Variable	Mean low norms	Mean medium norms	Mean high norms
Self-efficacy			
Personal skills biodiversity conservation	4.8	5.0	5.7
Damage prevention biodiversity	5.0	5.2	5.7
Find solutions for difficulties biodiversity conservation	5.0	5.1	5.7
Importance of farm income sources			
Farm sales	6.0	5.8	5.9
Biodiversity direct payments	4.3	5.0	5.7
Policy priority			
Promote biodiversity	3.7	4.6	5.4
Promote animal welfare	4.2	4.6	4.9
Reduce consumer prices	2.5	2.8	2.8
Ensure appropriate farm income	6.3	6.3	6.3
Increase domestic food production	6.2	6.1	5.7
Reduce greenhouse gas emissions	3.3	4.0	4.6
Reduce nutrient surplus	3.8	4.4	5.0
Reduce pesticide application	3.8	4.5	5.0
Socio-demographic characteristics			
Share males	90.0	92.7	89.1

(*continued on next page*)

Table B2 (*continued*)

Variable	Mean low norms	Mean medium norms	Mean high norms
Age farm manager	51.0	51.0	50.8
Share full-time farms	78.6	74.0	74.6
Share farms German-speaking region	85.6	82.6	82.6
Education			
Share practical experience	5.3	5.7	5.1
Share apprenticeship	0.4	0.0	0.3
Share federal vocational certificate	4.6	5.7	3.6
Share federal certificate of competence	45.0	46.8	42.5
Share professional experience	15.3	10.2	10.2
Share master's examination	18.7	21.1	23.2
Share higher college	3.4	3.4	6.0
Share university	2.7	4.5	6.3
Share other	4.6	2.6	2.7
Farm characteristics			
UAA	24.0	22.3	23.6
Livestock units per hectare	1.3	1.2	1.0
Share organic farms	14.8	18.1	29.7
Agricultural zone			
Share farms in valley zone	46.8	46.1	45.4
Share farms in hill zone	15.6	14.7	13.8
Share farms in mountain zone I	11.4	12.8	12.6
Share farms in mountain zone II	19.0	15.5	15.0
Share farms in mountain zone III	5.3	7.9	7.2
Share farms in mountain zone IV	1.9	3.0	6.0

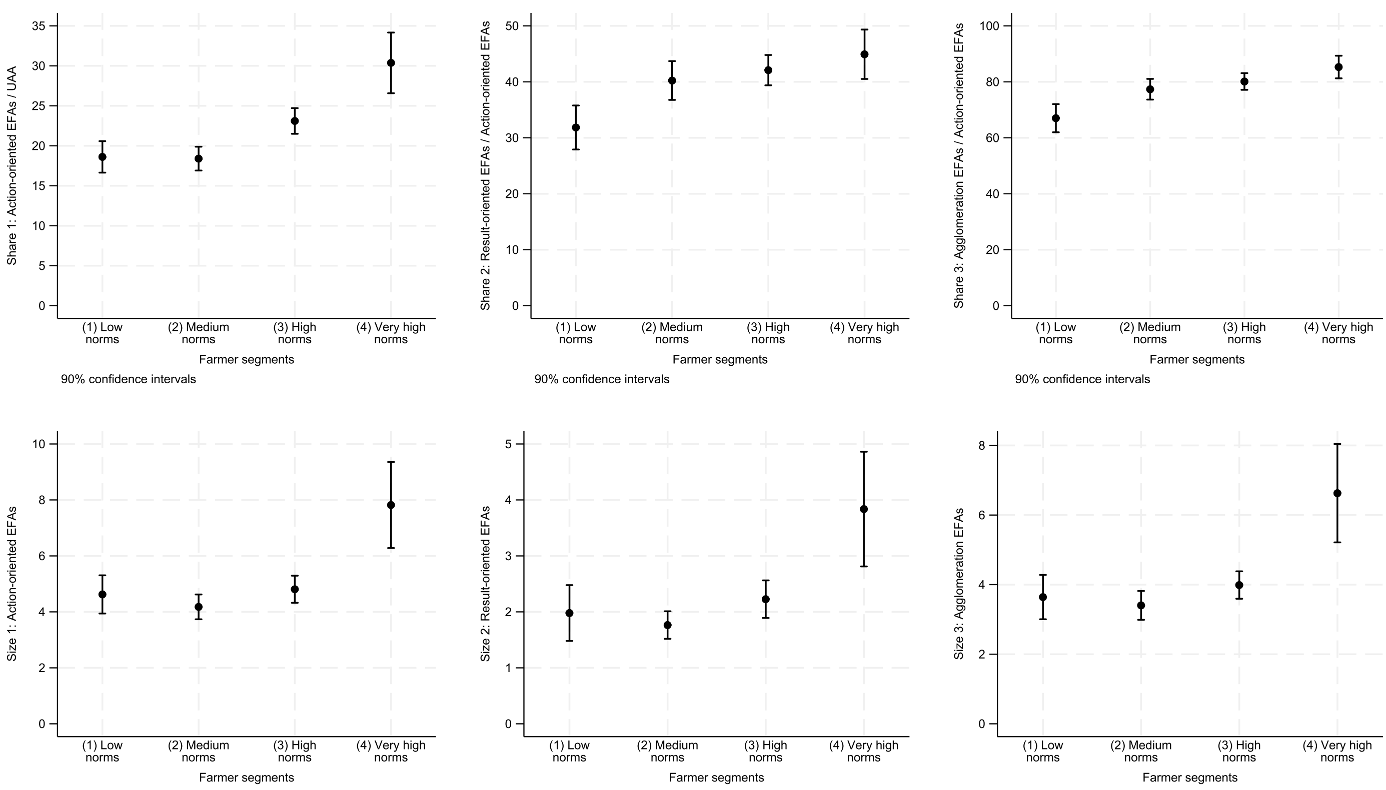

Fig. B2. Confidence interval plots visualizing the differences in the implementation of EFAs based on the $S = 4$ segment solution.

Table B3
Results of the ANOVA for EFA shares and EFA sizes based on the $S = 4$ segment solution.

Variable	Mean difference low norms – medium norms	Mean difference low norms – high norms	Mean difference low norms – very high norms	Mean difference medium norms – high norms	Mean difference medium norms – very high norms	Mean difference high norms – very high norms
EFA share						
Share 1	+0.2	−4.5**	−11.8***	−4.7***	−12.0***	−7.3***
Share 2	−8.4***	−10.3***	−13.1***	−1.9	−4.7	−2.8
Share 3	−10.3***	−13.1***	−18.3***	−2.8	−8.0***	−5.2*

(*continued on next page*)

Table B3 (*continued*)

Variable	Mean difference low norms – medium norms	Mean difference low norms – high norms	Mean difference low norms – very high norms	Mean difference medium norms – high norms	Mean difference medium norms – very high norms	Mean difference high norms – very high norms
EFA size						
Size 1	+0.4	+0.2	−3.2***	−0.6*	−3.6***	−3.0***
Size 2	+0.2	+0.2	−1.8***	−0.4*	−2.0***	−1.6**
Size 3	+0.2	+0.4	−3.0***	−0.6*	−3.2***	−2.6***

***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table B4
Mean values used in the ANOVA.

Variable	Mean low norms	Mean medium norms	Mean high norms	Mean very high norms
EFA share				
Share 1: (Action-oriented EFAs/UAA)	18.6	18.4	23.1	30.4
Share 2: (Result-oriented EFAs/Action-oriented EFAs)	31.8	40.2	42.1	44.9
Share 3: (Agglomeration EFAs/Action-oriented EFAs)	67.0	77.3	80.1	85.3
EFA size				
Size 1: Action-oriented EFAs	4.6	4.2	4.8	7.8
Size 2: Result-oriented EFAs	2.0	1.8	2.2	3.8
Size 3: Agglomeration EFAs	3.6	3.4	4.0	6.6

Data availability

The data that has been used is confidential.

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