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Not the average farmer: Heterogeneity in Dutch arable farmers' intentions to reduce pesticide use

Jaap Sok [a,*], Lieneke Bakker [b], Wopke van der Werf [c], Felix Bianchi [b]

[a] Business Economics, Wageningen University, Wageningen University and Research (WUR), Wageningen, the Netherlands
[b] Farming Systems Ecology Group, Wageningen University and Research (WUR), Wageningen, the Netherlands
[c] Centre for Crop Systems Analysis, Wageningen University and Research (WUR), Wageningen, the Netherlands

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ABSTRACT

Ambitious environmental policies and regulations in Europe aim to reduce pesticide use, yet their implementation faces significant obstacles. Effective strategies that gain support within the farming community require a deeper understanding of the underlying intentions, considering that farmers are a heterogeneous group with diverse beliefs related to socio-demographic characteristics. Using an existing dataset with theory of planned behaviour data from 359 Dutch arable farmers (Bakker et al., 2021), we examined the heterogeneity in intentions and beliefs regarding pesticide reduction. Expanding the analysis with quantile regression models, we show that the influence of attitude becomes increasingly important as farmers' aspirations to reduce pesticide use grow. Additionally, we observed a small positive effect of injunctive norms at the 25th quantile and a small negative effect at the 75th quantile of intention. These findings indicate that the relative impact of these constructs varies across the intention distribution, emphasising the need for more nuanced quantitative analyses of heterogeneity in TPB studies. Using moderation models, we observed variations in the relative impact of attitude, injunctive and descriptive norms on intention across different segments of the farming community, particularly concerning age, educational level, and farm income dependencies. Younger, higher-educated farmers, and those less reliant on farm income demonstrated greater openness towards reducing pesticide usage and adopting alternative crop protection practices. These findings suggest that different farmer segments may respond differently to interventions and incentives. Policymakers can leverage this knowledge to develop more nuanced and targeted strategies that promote pesticide reduction while aligning with the diverse motivations and beliefs present among farmers.

1. Introduction

The agri-food sector in the European Union (EU) plays a critical role in ensuring food security for millions of people while significantly contributing to the European economy, with an estimated gross value added of €220.7 billion in 2022. Particularly noteworthy is the fact that in certain regions, employment in the food supply chain constitutes more than 10 % of total employment (European Council, 2022). However, despite its pivotal role, the sector faces ongoing challenges posed by weeds, pests, and diseases, which incessantly threaten crop yields and quality (Savary et al., 2019).

In response to these challenges, farmers heavily rely on pesticides as a primary means to manage the risks associated with pests and diseases (Goulet et al., 2023). Nevertheless, the use of pesticides comes with its own set of concerns, as they can potentially pose adverse impacts on the environment and human health (e.g. Cech et al., 2023; Uhl and Brühl, 2019). Recognizing these risks, there is a growing emphasis on the need for policies aimed at mitigating these adverse effects by reducing pesticide usage, while simultaneously striving to achieve a balance between economic success, environmental sustainability, and social well-being.

In June 2022, the European Commission took a significant step in mitigating impacts from the use of pesticides by approving the proposal for the Sustainable Use of Plant Protection Products Regulation (SUR). This regulation was designed to establish binding legislation aligning with the EU Green Deal target. The ambitious aim of SUR was to cut down both the use and risk of chemically synthesised pesticides by 50 % before 2030. These are ambitious targets, but with farmers' getting to

* Correspondence to: Department of Social Sciences, Business Economics, Wageningen University, Hollandseweg 1, Wageningen, KN NL-6706, the Netherlands.
E-mail address: jaap.sok@wur.nl (J. Sok).

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the streets demonstrating on their tractors in major cities like Berlin, Paris and Amsterdam, initiatives for new policies aiming at pesticide reduction have been, at least temporarily, retracted. The SUR got rejected by the EU parliament in November 2023 (European Parlement, 2023). Critics argued that the proposed regulation lacked a thorough consideration of the potential impacts of pesticide reduction on European food security. Nevertheless, ten key policy objectives set for the period 2023 – 2027 of the Common Agricultural Policy do indicate a gradual shift and greater emphasis on environmental and social goals of agriculture, in addition to attaining economic goals (European Commission, 2021).

In the Netherlands, government and policy refrain from prescribing farmers a particular form of crop management, allowing them the flexibility to tailor their pest management strategies based on a variety of information sources and learning strategies. While some farmers show a high degree of autonomy in this regard, others rely more heavily on input from farm advisors and their social circle of peers (Barham et al., 2018; Läpple and Barham, 2019). Recent empirical research conducted by Bakker et al. (2021) in the Netherlands has shown that, on average, farmers are not unwilling to reduce pesticides but they are in need of successful examples and look at peers. Besides, farmers perceive a limited ability to act. Acknowledging their role as food producers, they agree on the importance of reducing pesticides but also indicate the need to manage the impacts of weeds, diseases and pests to ensure satisfactory crop yield and quality and attain a satisfactory and secure compensation for their labour and investments. But do farmers generally share similar perspectives on these matters?

The study of Bakker et al. (2021) is grounded in the theory of planned behaviour (TPB), which offers a systematic approach for collecting information through interviews and a survey, followed by statistical analysis. This approach helps to understand how psychological, social and contextual factors influence the intention (i.e. readiness) to adopt a specific behaviour – in this case, reducing pesticide use within a specified time frame. The TPB has proven effective in understanding behaviour and suggesting strategies for behavioural change in farming (Dessart et al., 2019; Klebl et al., 2023; Thompson et al., 2023). However, it is important to note that the study of Bakker et al. (2021) did not explore the heterogeneity in farmers' intentions to adopt pesticide reduction practices. We believe such analyses are particularly valuable for informing pesticide policy and addressing other relevant issues in agricultural and environmental sciences and policy research.

While the TPB has been recognised as a valuable tool for analysing farmer behaviour, the palette of techniques employed for analysing survey data and quantifying relationships has been limited thus far. The vast majority of studies employing the TPB in agricultural contexts rely heavily on conventional regression method approaches, which primarily estimate the mean response within a population (Sok et al., 2021). Unfortunately, these approaches give narrow answers in terms of main statistical effects at the conditional mean of the dependent variable and do not provide insight into the heterogeneity in responses across the farmer community. Consequently, these studies only report the relative impact of the attitude, subjective norms, and perceived behavioural control (PBC) at the mean of intention. For example, if subjective norm emerges as the main factor driving intention, intervention strategies may be tailored to target social dynamics, involving influential normative referents like farm advisors or fellow farmers. However, these recommendations overlook the heterogeneity within the respondent population, for example in terms of age, gender or education level, even though these factors are likely to influence pesticide use (Burton, 2014; Meunier et al., 2024). Therefore, there is promise in analysing data collected under the framework of TPB using techniques that focus more on estimating heterogeneity in responses.

In this study, we examine heterogeneity in Dutch farmers' intentions and beliefs to decrease their use of pesticides using the TPB framework. Building upon the previous work of Bakker et al. (2021), who utilised linear structural equation modelling to inform strategies for encouraging the adoption of sustainable agricultural practices, we expand the set of analyses by applying quantile regression models and moderated linear regression models. By leveraging these analytical techniques within the TPB framework, we aim to unravel some of the interplay of psychological, social, and contextual factors shaping Dutch farmers' intentions to reduce pesticide usage, thereby offering valuable insights for the development of targeted interventions and policy measures aimed at promoting sustainable agricultural practices.

Quantile regression models offer valuable information into how attitude, subjective norm and PBC influence intention across farmers with varying levels of motivation and readiness – from those with lower (25th quantile) to medium (median) and higher (75th quantile) levels of intention. The application of quantile regression to analyse cross-sectional Likert scale survey data within the TPB framework represents a novel contribution to the literature. While quantile regression methods have already been applied to data collected with an alternative model of individual decision making from social psychology (Chen et al., 2019) and to behavioural surveys (e.g. Agarwal et al., 2022; Bannor et al., 2021; Polemis and Spais, 2020), their utilisation within research on farmer behaviour is relatively unexplored.

Moderated linear regression models constitute a well-established research approach in TPB research (e.g. Harris and Hagger, 2007), although their application in studies on farmer behaviour remains less common. The TPB framework posits that background factors, i.e. the properties of the individual or the social group, should not directly influence intention or behaviour. Treating background factors as direct predictors of intention has been qualified as an improper use of the TPB framework (Hennessy et al., 2010; Sok et al., 2021). Instead, it is recommended to study the influence of background factors on intention as moderator variables, shaping the relationships between attitude, subjective norm, and PBC on intention (Sok et al., 2021).

The remainder of this paper is structured as follows. In Section 2, we first introduce the research approach including a short description of the TPB framework in relation to analysing heterogeneity. Section 3 provides details on the materials and methods used. Section 4 reports the results, and Section 5 presents a discussion and contains the concluding remarks.

2. TPB and heterogeneity in brief

The TPB was developed by Fishbein and Ajzen (1975) and Ajzen (1991) to address the limitations of using broad social attitudes to predict human behaviour. Rather than relying solely on general attitudes, they proposed that specific behaviours are best predicted by the intention to perform those behaviours. The TPB focuses on the controlled aspects of decision making, particularly behaviours that are goal-directed and steered by conscious self-regulatory processes. In the context of pesticide management, decisions are made within a business context, and these decisions can impact both the private farm business and the provisioning of environmental and social public goods.

Unlike the expected utility model, which assumes a fully rational decision maker, the TPB posits that decisions and actions are based on some measure of reasoning, meaning that individuals consider various factors when contemplating their options (Ajzen, 1996). The intention to perform a given behaviour, often the dependent variable (y-variable), is considered the most immediate antecedent and the best predictor of actual behavioural performance. The TPB proposed three key constructs that explain intention: *attitude towards the behaviour* – one's positive or negative evaluation of performing the behaviour; *Subjective norm* – perceptions of whether important others think they should perform the behaviour. These two constructs explain the motivational source of intention. The third construct, *perceived behavioural control* (PBC), explains behaviours that are not entirely under volitional control (Fishbein and Ajzen, 2010).

Attitude, subjective norm, and PBC are belief-based constructs. Attitude towards the behaviour is determined by beliefs about likely outcomes, weighted by the subjective values of these outcomes – an expectancy-value model aligned with subjective expected utility theory (Fishbein, 1963). Secondly, akin to the attitude model, subjective norm is shaped by normative beliefs about the expectations of significant social referents, weighted by the motivation to comply with them. Normative beliefs also extend to descriptive norms, reflecting perceived behavioural expectations of others, weighted by identification with these referents. Lastly, PBC is influenced by control beliefs regarding factors that facilitate or hinder behaviour performance, weighted by perceived control factor efficacy.

From a theoretical perspective, the TPB acknowledges that the effects of attitude, subjective norm, PBC, and their underlying beliefs on intention can vary across individuals. These beliefs are shaped by daily encounters, direct observations, acceptance of information from external sources like media, and inferences from past beliefs (Fishbein and Ajzen, 1975, 2010). As a result, the same behaviour might be perceived differently by different individuals, depending on their unique backgrounds and experiences, leading to varying effects on their intentions. Although the TPB does not specify the exact origins of beliefs about particular behaviours, it suggests that various background factors may play a role. In the TPB, background factors are defined as properties of the individual or social group (Fishbein and Ajzen, 2010). These factors, such as age, education, personality traits, and culture, are expected to influence behaviour indirectly through their impact on beliefs or may moderate the relationships among the TPB constructs (Sok et al., 2021).

3. Materials and methods

Fig. 1 visualises how, in line with these theoretical considerations, we propose to empirically analyse heterogeneity in the relative impact of TPB explanatory constructs on intention. We employ moderation analysis and quantile regression techniques to explore this heterogeneity, with results that can be compared to those obtained using conventional regression techniques that rely on the mean response within a population.

We provide a detailed description of the following: how the TPB constructs were validated (3.1), the sample and its characteristics (3.2), the selection and coding of moderators as background factors (3.3), and how we estimated the relative impact of the TPB explanatory constructs on intention using linear, quantile, and moderated linear regression models (3.4).

3.1. Validating TPB constructs

The application of TPB follows standardised steps (see e.g. Fishbein and Ajzen, 2010). First, the behaviour of interest is defined in terms of its Target, Action, Context, and Time elements (TACT, principle of compatibility). In our study, the behaviour was defined as 'Decreasing my use of environmentally harmful pesticides (Target and Action) within two years (Time)'. No specific Context element was provided when defining the behaviour. Without clearly defined Target and Action elements, it is impossible to measure attitudes, norms, and PBC toward

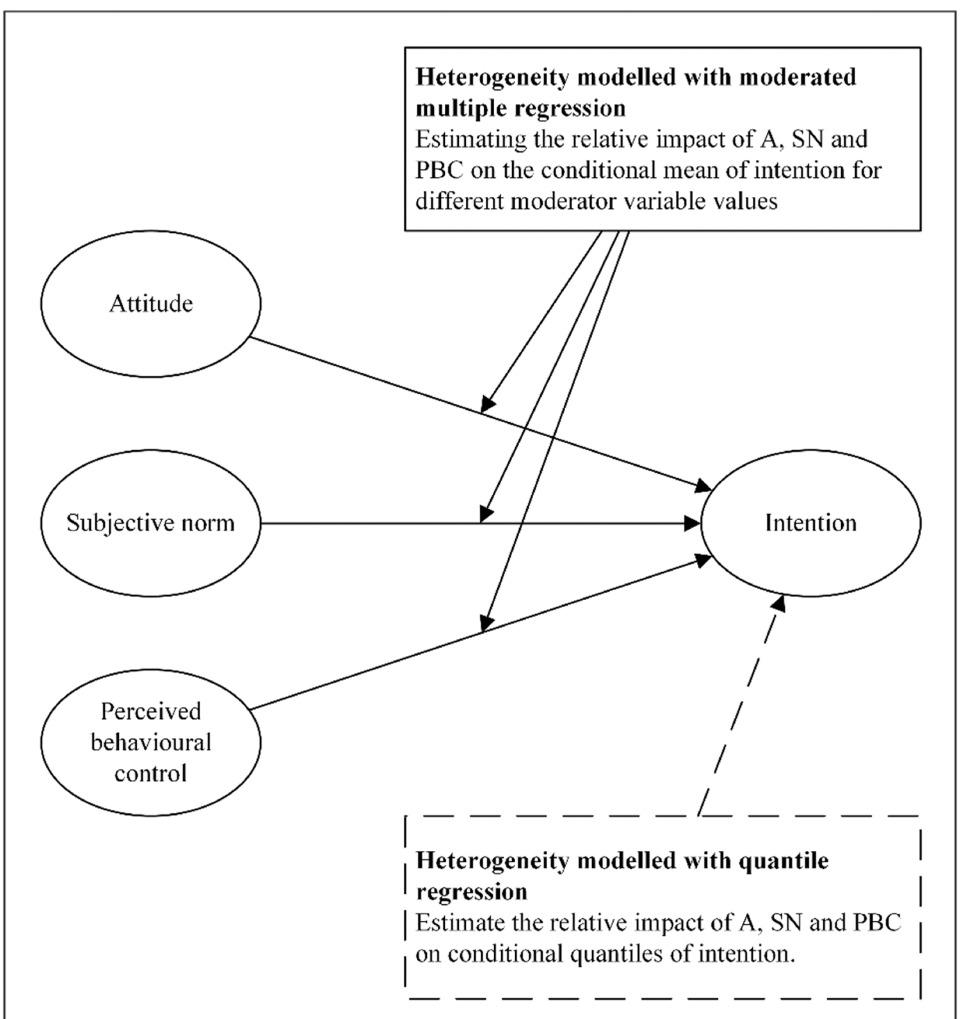

Fig. 1. Research approach for analysing heterogeneity in the effect of attitude (A), subjective norm (SN), and perceived behavioural control (PBC) on intention.

the behaviour. While the Context and Time elements can add specificity to the behaviour definition, the focus here was only on the temporal dimension. This definition of behaviour guided the formulation of items for reflective (direct) measures for the intention, attitude, injunctive and descriptive norms, and perceived behavioural control (PBC). The survey data was collected from February to May 2019. For details on the full measurement and data collection procedures, including how sample size was determined and the research ethics applicable at that time, we refer to Bakker et al. (2021).

From a measurement perspective, intention and its immediate determinants are unobservable constructs. A construct is a latent variable that can be defined in conceptual terms but cannot be directly measured or measured without error (Hair et al., 2010). Therefore, a confirmatory factor analysis (CFA) was conducted on the data collected from the sample of arable farmers to evaluate the validity of the TPB constructs. We assessed whether the reflective indicators correlated highly on the factor or latent variable that was a-priori expected to represent the same construct and not on factors representing other constructs. The model fit of the CFA was evaluated using recommended statistical tests (see e.g. Kline, 2011). Possible removal of reflective indicators and the respecification of the CFA were based on an inspection of modification indices and standardised residuals and on the calculation of validity statistics, i.e. the average variance extracted and composite reliability.

The measurement model results are given in Appendix A and confirm the factor structure in (Bakker et al., 2021). Accordingly, two sub-dimensions were distinguished within attitude towards the behaviour: general attitude (important, necessary and favourable) and risk attitude. Within the subjective norm, we distinguished injunctive norm (an individual's perception of what is socially or morally approved, or disapproved) and descriptive norm (an individual's perception of behaviour that is typical for members of the peer group). Several reflective indicators had to be removed to obtain a good model fit.

3.2. Sample characteristics

From the original sample outlined by Bakker et al. (2021), we selected the respondents who identified themselves as arable farmers. We then filtered out respondents demonstrating 'straightlining' response behaviour, a sign of respondents losing their motivation to engage with the survey (Kim et al., 2019). The final sample size was based on responses from 359 arable farmers. None of the respondents indicated they managed an organic farm.

To assess the representativeness of our sample, we can examine several key indicators. Our sample has a mean age of 52, with 48 % of respondents having attained higher education (either at the higher professional education or university level). Additionally, the average farm size in our sample is 85 ha. These characteristics closely align with those reported by Sok and Hoestra (2023), who surveyed 81 Dutch arable farmers in 2020. Their study found a mean age of 53, with 46 % of respondents having higher education, and an average farm size of 88 ha. While our sample mirrors these figures closely, it's essential to note that they may not fully capture the entire population of arable farmers, possibly due to a coverage error that is inherent in online survey methodologies. According to CBS Statline (2024), which provides census data on the ageing of farmers in the Netherlands, less than 10 % of arable farms are managed by farmers younger than 40 years old, while over 25 % are managed by farmers older than 67, which is the typical retirement age for Dutch employees. Moreover, data from the Dutch Farm Accountancy Data Network (Wageningen Economic Research, 2019) suggests that the average size of a Dutch arable farm was 61.8 ha in 2019. In summary, while our sample characteristics closely resemble those of similar studies, it is important to acknowledge that they may not fully represent the entire population of Dutch arable farmers.

Table 1 presents a breakdown of the sample by age cohorts. The socio-demographic data in the first section reveal that younger arable farmers, just as in the census data (Statline, 2024), tend to have higher

Table 1
Overview of characteristics and responses of 359 arable farmers in The Netherlands.

Age (years)	'40 years or younger'	'41 – 50 years'	'51 – 60 years'	'61 years or older'	All
Number of respondents	59 (16.4 %)	88 (24.5 %)	133 (37.0 %)	79 (22.0 %)	359 (100 %)
1. Socio-demographics					
Higher education[a]	0.68	0.49	0.41	0.33	0.46
Farm size[b]	107.8	98.6	81.5	56.8	85.0
Income from farming[c]	74.7	82.3	78.8	72.8	77.8
2. Main indicator score per TPB construct[d]					
I am willing to… (intention – i1)	3.0	3.2	3.0	2.9	3.0
Unimportant – important (attitude – i4)	3.5	3.4	3.4	3.5	3.5
Risky – not risky (attitude – a3)	1.7	1.9	1.9	2.1	1.9
People who have much to do with my farm (injunctive norms – in1)	2.5	2.9	2.9	2.7	2.8
Colleague-farmers will (descriptive norms – dn1)	2.7	3.0	2.8	2.8	2.8
If I wanted to, I could (perceived behavioural control – pbc1)	2.6	2.4	2.6	2.7	2.6
3. Self-identify[d]					
I see myself as an environmentally conscious farmer	4.1	4.1	3.9	3.9	4.0
4. Perceived manageability of…[e]					
diseases	2.7	2.5	2.6	2.9	2.7
pests	2.8	2.4	2.6	3.0	2.6
weeds	2.6	2.4	2.4	2.7	2.5
5. Crop protection information source use[f]					
Dialogues with crop advisors	0.76	0.81	0.72	0.68	0.74
Dialogues with suppliers of crop protection products	0.37	0.44	0.46	0.41	0.43
Dialogues with colleagues or study club members	0.53	0.38	0.32	0.30	0.36
Open days, demonstration fields, excursions	0.32	0.39	0.35	0.35	0.36
Articles from agricultural professional magazines	0.24	0.19	0.29	0.34	0.27

[a] shown as fraction of farmers,
[b] shown as mean of number of hectares, 16 missing values,
[c] shown as mean of percentage income, 47 missing values,
[d] shown as mean of score from 1 = disagree to 5 = agree,
[e] shown as mean of score from 1 = difficult to 5 = easy,
[f] respondents had to select the three most preferred from a list of twelve information sources. We show here the fractions of the five most preferred sources based on the full sample.

levels of education and manage larger arable farms compared to their older counterparts. About three-quarters of the household income results is derived from farming activities, with no remarkable differences observed between age groups. The subsequent section reports the mean values of the main reflective indicator of each TPB construct. We refer to Appendix A for information on all indicators used to represent the constructs. We find here that farmers exhibited a moderate intention to reduce pesticide use (with mean values around 3). In attitudes towards reducing pesticide use, younger farmers tend to score a bit higher on the risk considerations. Younger farmers who are still in the entry stage of farming may less likely accept situations of a higher risk of reduced yields or more difficulties with controlling pests (see also section 2.3). They also tend to score lower on perceived social pressures from injunctive norms to reduce pesticide use.

Sections 3 and 4 report farmers' self-perceptions of environmental consciousness and their assessments of the manageability of diseases, pests, and weeds on their farms. The age cohort '41 – 50 years' stands out most with the highest average score on the self-identity indicator and lowest scores on perceived manageability, but differences across age cohorts are small. In Section 5, we report farmers' preferences for information sources about crop protection developments. The information source 'dialogues with crop advisors' is the most preferred information source across all groups. However, preferences for the second and third most preferred sources differ among age cohorts.

3.3. Selection of moderators and dummy coding

The TPB conceptual framework suggests a set of potentially influential background factors, defined as properties of the individual or the social group, such as gender, age, education, personality traits, values, intelligence, sensation seeking, religion, culture, etc. (Fishbein and Ajzen, 2010). We conceptualise the role of background factors as moderators. Moderation is a situation in which the relationship between two constructs depends on the values of a third variable, referred to as a moderator variable (Hair et al., 2021). For example, in a TPB context, we may evaluate how the age of the farmer affects the relationship between attitude and intention. The background factors (socio-demographics) selected from the survey for this study were: the age of the farmer, educational level, and dependency on farm income.

Farmer socio-demographics are essential to understanding heterogeneity in farmer perceptions and beliefs, but these relationships can be multi-faceted and complex (Burton, 2014). Cognitive abilities, for example, change with age and affect the way decision makers engage in complex decisions. In return for decreasing abilities to process information, older farmers can rely on increased experience and associated knowledge, better emotion regulation, and selective motivation (De Bruin, 2017). Age may also represent a cohort effect. Each generation develops its values and attitudes as a result of general tendencies in society that change over time. This includes the view on the role and use of pesticides in food production, which may also change with the level and type of education a farmer has obtained. The view on pesticide use may also change with the level and type of education a farmer has obtained. The age can also reflect the life cycle stage the farm is in (Kay et al., 2016). Farmers in an entry stage with financial constraints are less likely to accept situations of a higher risk of reduced yields or more difficulties with controlling pests (Gale Jr., 1994). Farm income dependency may also explain heterogeneity in motivations and ability to reduce pesticide use. Farmers who derive a higher share of their income from farm business activities may be more risk-averse and less willing to experiment with alternative pest management methods (Bontemps et al., 2021).

We chose to group the farmers into different categories for analysing the moderating effect of age, educational level, and farm income dependency on the TPB's hypothesised relationships. This way, we could compare the effects of different age groups, education, and farm income dependency levels more easily and avoid potential problems with outliers or non-linear relationships. Fig. 2 shows the base cut-off values chosen for age and farm income dependency.

For age, the following base categorisation was made: '40 years or younger' (16.4 % of the sample), '41 – 50 years' (24.5 % of the sample), '51 – 60 years' (37.0 % of the sample) and '61 years or older' (22.0 % of the sample). Some justification for this categorisation is that the age of 40 years is a relevant cut-off value as it is the maximum upper age limit for the young farmer definition in the EU. The CAP 2023–27 provides several forms of financial support for 'Young farmers' (European Commission, 2022). Another justification is that each age group should contain sufficient respondents to be able to conduct the statistical analyses. Nevertheless, there is a certain degree of arbitrariness in whichever categorisation is chosen.

The second moderator was the farmer's educational level. Two dummy variables were created for education: 'secondary vocational or lower' (54.3 % of the sample) and 'higher vocational or university' (45.7 % of the sample). We were not able to make categorisations based on the type of education obtained.

For farm income dependency, the following base categorisation was made: 'less than 80 %' (34.3 % of the sample), '81–99 %' (27.8 % of the sample), and '100 %' (37.8 % of the sample).

3.4. Estimating the relative impact of TPB explanatory constructs on intention

We first estimated the relative impact of attitude, subjective norm, and *PBC* on the conditional mean of intention (*I*), i.e. in line with the conventional application of TPB also applied in Bakker et al. (2021). Note that attitude is broken into two sub-dimensions A and A_{risk} and subjective norm consists of injunctive (*IN*) and descriptive norms (*DN*) (see section 2.1). The corresponding mean regression equation is:

$$I = \beta_1 A + \beta_2 A_{risk} + \beta_3 IN + \beta_4 DN + \beta_5 PBC + \varepsilon. \tag{1}$$

In Eq. (1), β_1-β_5 are the coefficients that indicate the strength of the relationships between the respective variables and intention, and ε is the error term. This equation was estimated in a structural equation modelling (SEM) framework and as a linear regression model.[1] If model results from both approaches give the same interpretation, we use the latter to contrast results with those from quantile regression and moderated linear regression models to evaluate heterogeneity.

Quantile regression models are useful to explore if the conditional distribution of the dependent variable is well captured by its mean alone. The second step was therefore to estimate the relative impact of attitude, subjective norm, and PBC on three conditional quantiles of intention (25, 50 and 75 percentile):

$$Q_\tau(I) = \gamma_1(\tau)A + \gamma_2(\tau)A_{risk} + \gamma_3(\tau)IN + \gamma_4(\tau)DN + \gamma_5(\tau)PBC + \varepsilon_\tau. \tag{2}$$

In Eq. (2), $Q_\tau(I)$ represents the τ-th quantile of intention. $\gamma_{1\tau}$-$\gamma_{5\tau}$ are the coefficients that indicate the strength of the relationships between the respective variables and the τ-th quantile of the intention. ε_τ is the error term for the τ-th quantile that captures the differences between observed values and the predicted values at the τ-th quantile. Unlike in mean regression models, where the error term is assumed to follow a normal distribution and is symmetrically distributed around zero, the error term in quantile regression is not assumed to

[1] A Structural Equation Modelling (SEM) estimates the parameters of both the measurement model and the structural model simultaneously using maximum likelihood estimation, without a loss of information. However, most SEM software packages do not support adding moderation effects, such as between the latent variable Perceived Behavioural Control (PBC) and the observed variable age. Estimating conditional quantiles is therefore not possible within these frameworks. For Linear Regression (LR), Quantile Regression (QR), and Moderated Linear Regression (MLR) models, factor scores calculated from the CFA model were used.

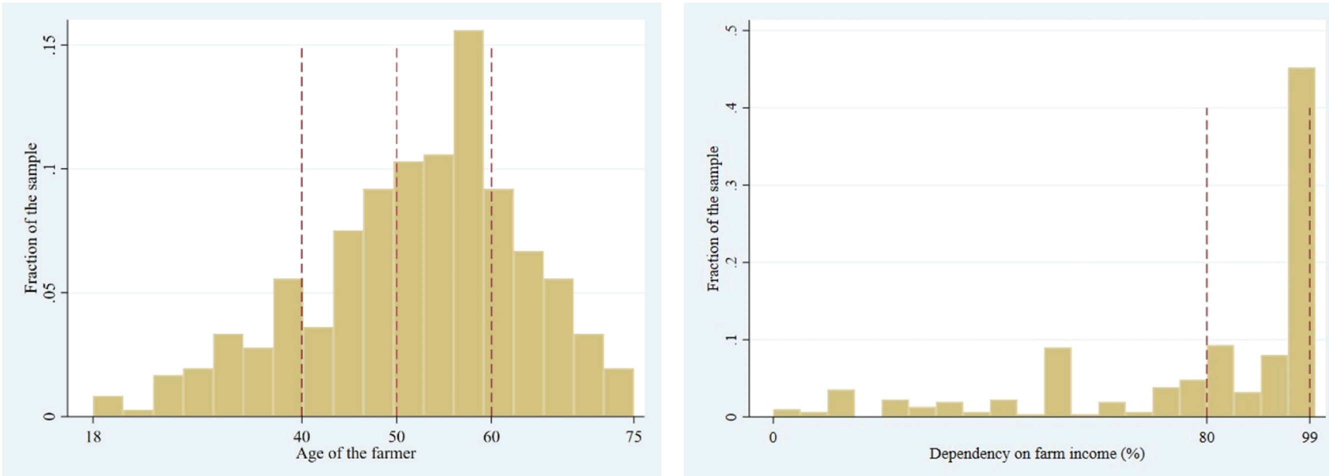

Fig. 2. Histograms of farmers' age and their dependency on farm income and suggested cut-off values for creating dummy variables.

follow any specific distribution. We refer to Hao and Naiman (2007) for an introduction to quantile regression for the social sciences and more information on the least absolute deviations estimator. We utilised Stata's built-in *sqreg* command and obtained confidence intervals using 100 bootstrap replications.

Heterogeneity in effects using quantile regression is evaluated by testing the equality of the coefficients at different quantiles and by inspecting if the quantile regression coefficients fall outside the confidence interval of linear regression outcomes. In this way, we could assess whether the effects of the TPB explanatory constructs vary along the distribution of intention.

The third step is to estimate moderated linear regression models that give the relative impact of attitude, subjective norm, and PBC on the conditional mean at different values of a moderator variable. We had three moderator variables of interest (see section 2.3), thus estimated three equations. The equation for the age of the farmers as the moderator is:

$$I = \beta_{1j}A_1x_j + \beta_{2j}A_2x_j + \beta_{3j}A_3x_j + \beta_{4j}A_4x_j + \varepsilon \quad (3)$$

where β_{ij} is the estimated regression coefficient for age group i, A_i is a dummy variable for age with value 1 for age group i and 0 otherwise, while x_j is one of the explanatory constructs A, A_{risk}, IN, DN, and PBC. We specified the dummy moderator variables following the partition approach to ease the interpretation of dummy variables and their interaction effects (Yip and Tsang, 2007). In this model, the regression coefficient for the construct x_j is made dependent on the age group, as in a conventional interaction, but without including the effect of age in the intercept of the model. Heterogeneity in effects is assessed by testing the equality of the regression coefficients β_{ij}, which represents the effect of

Table 2
LR and QR regression model estimates of the effect of attitude, subjective norms and perceived behavioural control on intention to decrease pesticide use.

Regression Type	Predictor	Coefficient (B)	Standard Error (SE)	p-value	95 % Confidence Interval (CI)
LR					
	A	0.32	0.06	<0.001	[0.20, 0.43]
	A_{RISK}	−0.14	0.05	0.005	[−0.23, −0.04]
	IN	−0.00	0.05	0.963	[−0.09, 0.09]
	DN	0.54	0.05	<0.001	[0.44, 0.65]
	PBC	0.34	0.04	<0.001	[0.26, 0.41]
QR (q25)					
	A	0.27	0.09	0.003	[0.09, 0.44]
	A_{RISK}	−0.12	0.06	0.031	[−0.23, −0.01]
	IN	0.10	0.07	0.162	[−0.04, 0.24]
	DN	0.55	0.08	<0.001	[0.39, 0.70]
	PBC	0.31	0.07	<0.001	[0.17, 0.45]
QR (q50)					
	A	0.32	0.09	<0.001	[0.15, 0.50]
	A_{RISK}	−0.12	0.05	0.019	[−0.21, −0.02]
	IN	−0.01	0.05	0.792	[−0.12, 0.09]
	DN	0.61	0.10	<0.001	[0.41, 0.81]
	PBC	0.34	0.06	<0.001	[0.21, 0.46]
QR (q75)					
	A	0.49	0.07	<0.001	[0.35, 0.63]
	A_{RISK}	−0.15	0.06	0.011	[−0.26, −0.03]
	IN	−0.11	0.06	0.056	[−0.22, 0.00]
	DN	0.52	0.07	<0.001	[0.39, 0.65]
	PBC	0.34	0.05	<0.001	[0.25, 0.44]

A = general attitude, A_R = risk attitude, IN = injunctive norms, DN = descriptive norms, PBC = perceived behavioural control.
LR = linear regression, QR = quantile regression.
n = 359
Coefficients in the grey shaded cells were significantly different from each other according to an F-test
LR: R^2 = 0.70, adj. R^2 = 0.69. See also Fig. 3.
QR: a simultaneous quantile regression model was run with 100 bootstrap replications. pseudo R^2 = 0.52 (q25), 0.48 (q50), 0.44 (q75).

each TPB explanatory construct on the intention for different farmer age cohorts.

4. Results

The results in Table 2 together indicate that social pressures from descriptive norm are the main driver of intention. The linear regression model results[2] indicate that, at the mean level of intention to reduce pesticide use, PBC and attitude are also important drivers of intention, whereas social pressures from injunctive norms and risk attitude are not when controlling for the other constructs' effects. To evaluate heterogeneity, we inspect with Fig. 3 if the quantile regression coefficients fall outside the confidence interval of linear regression model outcomes.

While the quantile regression results confirm that descriptive norm is the most influential construct in explaining intention, they also reveal that the relative impact of attitude and injunctive norm varies across quantiles. The effect of attitude increases at higher quantiles of the intention to reduce pesticide use. While the effect of injunctive norm is insignificant at the mean or the median of intention, we observed a small positive effect at the 25th quantile of intention and a small negative effect at the 75th quantile of intention. Equality tests indicate that the effects of attitude ($F_{2,\ 353} = 2.65, p < 0.10$) and injunctive norms ($F_{2,\ 353} = 3.55, p < .05$) varied significantly across quantiles.

The results of the moderated linear regression model with age, as presented in Table 3, reveal that intention was significantly influenced by attitude across all age groups of farmers, except for those aged 61 years or older. Similarly, descriptive norm was the main determinant of intention across all age groups, except for farmers aged 61 years or older. In this group with older farmers, injunctive norms exhibited a strong positive effect on intention, whereas attitude did not increase intention and descriptive norm had a smaller effect than injunctive norm. The effect of PBC on intention did not vary across age groups. Risk attitude generally demonstrated small and insignificant negative effects on intention. Some of the coefficients in Table 3 are negative, which signals the presence of shared variance (collinearity) among the independent variables as univariate analyses showed that the effect of each construct on intention individually was positive.

The model findings with age as the moderator suggest that in particular the influence of attitude ($F_{3,\ 338} = 2.36,\ p < .10$) and injunctive norm ($F_{3,\ 338} = 9.25, p < .0001$) on intention are not the same across farmer generations. Thus, the intention to reduce pesticide use of younger farmers is driven most by attitude, whereas in older farmers it is mainly the subjective norm. These findings can be complemented with findings on how attitudinal, normative, and control beliefs differ across age groups (Appendix C).

Some of the injunctive normative beliefs varied considerably among age groups. The crop advisor is an influential normative referent for older farmers but not so much for younger farmers. Farmers in different age cohorts also tend to think differently about the normative influence of colleague farmers who grow crops organically. Farmers in different age groups also think differently about the impact of changing weather conditions as a factor that hinders them in reducing their pesticide use.

Table 4 shows that the education level of farmers only affects how much they are influenced by descriptive norm, as shown by the significant difference in the coefficients ($F_{1,\ 348} = 3.74,\ p < .10$). Higher educated farmers have higher intentions to reduce pesticide use if they see others doing the same, which means they are more open to learning from practices implemented by others that can lower pesticide use.

The analysis of which beliefs vary across education levels (Appendix D) indicate that higher educated farmers look more at what organic farmers do in terms of crop protection. The mean scores on attitudinal beliefs regarding the expected consequences of reduced pesticide use were also significantly higher for higher-educated farmers. These beliefs pertained to the effects of reduced pesticide use on crop quality, yields, and ability to control pests. These farmers also more strongly believe that improved plant breeding and the increased availability of alternative plant protection products are important enablers for reducing their pesticide use.

Farm income dependency also moderates the effects of attitude, subjective norm, and PBC on intention (Table 5). Most notably the risk attitude coefficients across farm income segments are significantly different from each other ($F_{1,\ 301} = 4.59, p < .05$). This means that households that depend more on farming income perceive reducing pesticide use as more risky. The reported risk attitude coefficients are negative, which signals the presence of shared variance (collinearity) among the independent variables, as univariate analyses showed that the effect of risk attitude (less risky) on intention was positive. We also observed that farmers who are less reliant on their farm income pay more attention to what organic farmers do regarding crop protection (Appendix E). Having financial constraints leads to less consideration of alternative crop protection methods and more dependence on pesticide use.

5. Discussion and conclusions

Are farmers unified in their perspectives and motivations for reducing pesticide usage? Can policy makers adopt a uniform approach to encourage the adoption of alternative crop protection methods? Our study delved into these questions by investigating the heterogeneity in intentions and beliefs among Dutch arable farmers regarding pesticide reduction. Our analyses yield quantitative evidence of significant heterogeneity in these intentions and beliefs, which was associated with individual, external, and social factors (Meunier et al., 2024). By applying the theory of planned behaviour (TPB), we found that intentions and their determinants to reduce pesticide use vary significantly across different segments of the farming community. While our regression models corroborate Bakker et al. (2021)'s findings that descriptive norm is the most important construct in explaining intention, our quantile regression results reveal that the effects of attitude and injunctive norm vary across different levels of intention.

Our moderation analyses show that younger, higher-educated, and/or less farm income-dependent farmers exhibit greater openness to reducing pesticide usage and adopting alternative crop protection methods compared to their older, lower-educated, and/or more farm income dependent counterparts. Furthermore, the crop advisor is an influential normative referent for older farmers, whereas younger, higher-educated, and/or less farm income dependent farmers are more inclined to consider the impact of climate change on arable farming. Higher-educated farmers consider more the potential economic consequences of changing production practices and emphasize more the importance of alternatives such as different breeds and plant protection products. Their intentions are more shaped by descriptive norms rather than injunctive norms, leading them to look to practices like those of organic farmers for inspiration. This offers scope for approaches to foster farmer learning to support the adoption of more sustainable farming practices (Chantre and Cardona, 2014; Wang et al., 2023b).

Social learning and training are just some of the possible interventions for behaviour change. Our findings indicate that interventions and policies aimed at influencing farmers' pesticide management should match the specific needs and preferences of each segment. Therefore, a combination of targeted instruments is necessary to encourage adoption, rather than relying on a generic strategy for the entire farmer population (Hofmann et al., 2023; Pedersen et al., 2020).

[2] Largely consistent interpretations, with similarly sized effects, were obtained from both the Structural Equation Model (SEM) and the Linear Regression (LR) model results (see Appendix B). However, for risk attitude, the models diverged, with LR showing a significant effect and SEM showing a non-significant one, possibly due to the handling of measurement error (see also footnote 1). Given the overall consistency, we used LR model results to contrast with those from the Quantile Regression (QR) model.

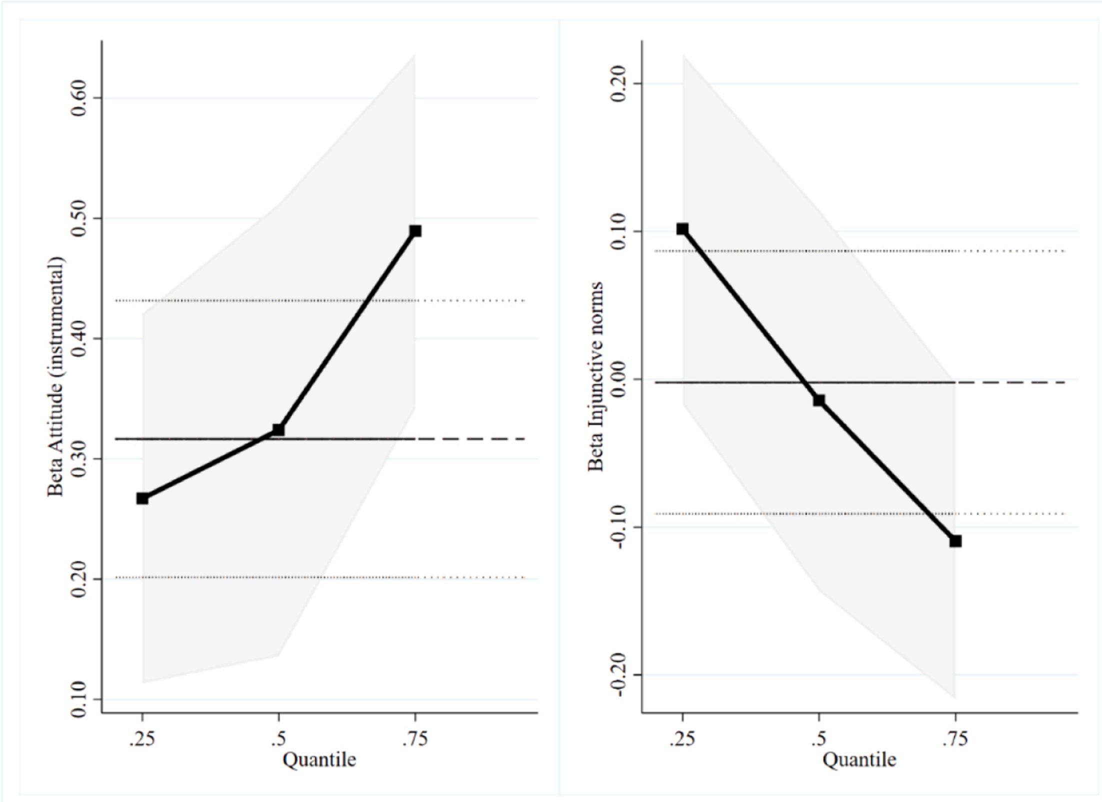

Fig. 3. QR and LR regression coefficients and confidence interval of attitude and injunctive norms. Line with square markers and grey confidence interval are QR model estimates. Solid and dashed horizontal lines are LR model estimates.

Several frameworks offer classifications of policy categories and intervention functions, allowing for the selection of approaches based on the behavioural factors driving the behaviour of interest. Notable examples include the carrot-stick-sermon classification (Bemelmans-Videc et al., 2011; Rothschild, 1999) and the behavioural change wheel (Michie et al., 2011).

Several intervention functions focus on changing behaviour through reasoned opinions, such as education, persuasion and training, which require openness and a favourable attitude towards the behaviour. Different attitudes towards pesticide use act as lenses through which new information is searched, selected and interpreted (Lichtenberg and Zimmerman, 1999). Information that aligns with prior beliefs is more likely to be accepted, while information that contradicts these beliefs is often rejected – phenomena known as ‘confirmation bias’ and ‘motivated reasoning’ (Johnson et al., 2018). Based on our findings, persuasion and information campaigns may be most effective when targeting younger farmers through professional or interest groups, where they can learn about innovations such as integrated pest management, biodiversity restoration or crop diversification. Younger farmers, who may be more receptive to new practices, could be engaged through digital platforms and social media, where they can access educational resources and participate in virtual discussions (e.g. Rust et al., 2022; Skaalsveen et al., 2020). In contrast, more traditional farmers might be better reached through local agricultural extension services, where face-to-face interactions and hands-on demonstrations are emphasized.

It is also important to note that the effectiveness of many policy categories and interventions is often contingent on high levels of social capital, such as the presence of strong social networks and a culture of solidarity. The impact of education and persuasion interventions on farmers’ pesticide use behaviour can be leveraged by social influence, which refers to how the opinions and actions of others can shape individual beliefs and decisions. Once innovations are adopted by some pioneers within social networks, they could spread throughout the arable sector. For policy implications, it is important to know which ’social influencers’ have the most impact on pest and disease management decision making of the farmer (Wang et al., 2023b). Research in the Swiss agricultural context has revealed intriguing patterns: farmers advised by private extension services tend to use more pesticides, whereas those advised by public extension services favour preventive measures like nets for pest control (Wuepper et al., 2021). For changing pesticide use behaviour, interventions may, therefore, also focus on changing the physical or social context (Michie et al., 2011; Wiedemann and Inauen, 2023). So-called “environmental restructuring” may pertain to social and organisational changes, such as ensuring that farmers have better access to unbiased, public advisory services that prioritize sustainable practices. This could involve reallocating resources to strengthen public extension services to, for example, increase the availability of training on integrated pest management (IPM) techniques. Environmental restructuring can also involve adjusting the choice architecture, as targeted by nudges, to make sustainable practices the more straightforward or preferred options. Some researchers have studied farmers’ pesticide use from a habitual or routine perspective and suggest behaviour change strategies to focus on these aspects (e.g. Abadi, 2018; Kaiser et al., 2024).

In this study, we adopted a comprehensive survey approach to analysing heterogeneity within the TPB framework by estimating quantile regression models alongside three moderated linear regression models with one socio-demographic each. Our results highlight the nuanced insights that quantile regression models offer compared to mean regression models within social-psychological frameworks of individual behaviour (Chen et al., 2019). While our approach sheds light on various facets of heterogeneity, further exploration could prove fruitful. One promising avenue is the utilization of a latent class moderation model (Nylund-Gibson et al., 2022) capable of

Table 3
Results of linear regression (LR) and moderated linear regression (MLR) model with age, estimating the effects of constructs from the Theory of Planned Behaviour (TPB) on the intention of Dutch arable farmers to reduce pesticide use. For explanation of variable names, see table footnotes.

Regression Type	Predictor	Coefficient (B)	Standard Error (SE)	p-value	95 % Confidence Interval (CI)
LR	A	0.32	0.06	<0.001	[0.20, 0.43]
	A_{RISK}	−0.14	0.05	0.005	[−0.23, −0.04]
	IN	−0.00	0.05	0.963	[−0.09, 0.09]
	DN	0.54	0.05	<0.001	[0.44, 0.65]
	PBC	0.34	0.04	<0.001	[0.26, 0.41]
MLR	A				
	× ≤40 years	.35	0.16	0.032	[0.03, 0.67]
	× 41–50 years	.48	0.11	<0.001	[0.25, 0.70]
	× 51–60 years	.31	0.10	0.001	[0.12, 0.50]
	× ≥61 years	.03	0.13	0.815	[−0.21, 0.28]
	A_{RISK}				
	× ≤40 years	−0.12	0.13	0.354	[−0.39, 0.14]
	× 41–50 years	−0.13	0.08	0.140	[−0.29, 0.04]
	× 51–60 years	−0.19	0.08	0.020	[−0.35, −0.03]
	× ≥61 years	−0.10	0.10	0.324	[−0.30, 0.10]
	IN				
	× ≤40 years	0.08	0.10	0.423	[−0.12, 0.29]
	× 41–50 years	−0.26	0.09	0.003	[−0.43, −0.09]
	× 51–60 years	−0.05	0.07	0.522	[−0.19, 0.10]
	× ≥61 years	0.46	0.11	<0.001	[0.24, 0.67]
	DN				
	× ≤40 years	0.55	0.14	<0.001	[0.28, 0.82]
	× 41–50 years	0.64	0.10	<0.001	[0.45, 0.84]
	× 51–60 years	0.51	0.09	<0.001	[0.34, 0.68]
	× ≥61 years	0.33	0.11	0.004	[0.11, 0.55]
	PBC				
	× ≤40 years	0.30	0.10	0.003	[0.10, 0.50]
	× 41–50 years	0.34	0.07	<0.001	[0.21, 0.48]
	× 51–60 years	0.39	0.07	<0.001	[0.26, 0.52]
	× ≥61 years	0.30	0.07	<0.001	[0.15, 0.44]

A = general attitude, A_R = risk attitude, IN = injunctive norms, DN = descriptive norms, PBC = perceived behavioural control.
LR = linear regression, MLR = moderated linear regression.
n = 359
Coefficients in the grey shaded cells were significantly different from each other according to an F-test
LR: $R^2 = 0.70$, adj. $R^2 = 0.69$.
MLR with age: $R^2 = 0.73$, adj. $R^2 = 0.71$.

Table 4
Results of linear regression (LR) and moderated linear regression (MLR) model with education, estimating the effects of constructs from the Theory of Planned Behaviour (TPB) on the intention of Dutch arable farmers to reduce pesticide use. For explanation of variable names, see table footnotes.

Regression Type	Predictor	Coefficient (B)	Standard Error (SE)	p-value	95 % Confidence Interval (CI)
LR	A	0.32	0.06	<0.001	[0.20, 0.43]
	A_{RISK}	−0.14	0.05	0.005	[−0.23, −0.04]
	IN	−0.00	0.05	0.963	[−0.09, 0.09]
	DN	0.54	0.05	<0.001	[0.44, 0.65]
	PBC	0.34	0.04	<0.001	[0.26, 0.41]
MLR	A				
	× secondary vocational or lower	0.33	0.08	<0.001	[0.17, 0.49]
	× higher vocational or university	0.31	0.08	<0.001	[0.14, 0.48]
	A_{RISK}				
	× secondary vocational or lower	−0.13	0.06	0.044	[−0.26, −0.00]
	× higher vocational or university	−0.14	0.07	0.058	[−0.28, 0.00]
	IN				
	× secondary vocational or lower	0.05	0.06	0.439	[−0.08, 0.17]
	× higher vocational or university	−0.06	0.06	0342	[−0.19, 0.07]
	DN				
	× secondary vocational or lower	0.45	0.07	<0.001	[0.31, 0.59]
	× higher vocational or university	0.65	0.08	<0.001	[0.50, 0.80]
	PBC				
	× secondary vocational or lower	035	0.05	<0.001	[0.25, 0.45]
	× higher vocational or university	0.31	0.06	<0.001	[0.20, 0.42]

A = general attitude, A_R = risk attitude, IN = injunctive norms, DN = descriptive norms, PBC = perceived behavioural control.
LR = linear regression, QR = quantile regression.
n = 359
Coefficients in the grey shaded cells were significantly different from each other according to an F-test
LR: $R^2 = 0.70$, adj. $R^2 = 0.69$.
MLR with education: $R^2 = 0.70$, adj. $R^2 = 0.69$.

Table 5
Results of linear regression (LR) and moderated linear regression (MLR) model with farm income dependency, estimating the effects of constructs from the Theory of Planned Behaviour (TPB) on the intention of Dutch arable farmers to reduce pesticide use. For explanation of variable names, see table footnotes.

Regression Type	Predictor	Coefficient (B)	Standard Error (SE)	p-value	95 % Confidence Interval (CI)
LR[1]	A	0.32	0.06	<0.001	[0.20, 0.43]
	A_{RISK}	−0.14	0.05	0.005	[−0.23, −0.04]
	IN	−0.00	0.05	0.963	[−0.09, 0.09]
	DN	0.54	0.05	<0.001	[0.44, 0.65]
	PBC	0.34	0.04	<0.001	[0.26, 0.41]
MLR[2]	A				
	× ≤79 per cent	0.28	0.10	0.009	[0.07, 0.48]
	× 80 – 99 per cent	0.38	0.13	0.004	[0.12, 0.63]
	× 100 per cent	0.30	0.10	0.002	[0.11, 0.49]
	A_{RISK}				
	× ≤79 per cent	−0.31	0.09	0.001	[−0.49, −0.12]
	× 80 – 99 per cent	−0.07	0.09	0.419	[−0.24, 0.10]
	× 100 per cent	−0.07	0.09	0.417	[−0.25, 0.10]
	IN				
	× ≤79 per cent	−0.04	0.08	0.642	[−0.20, 0.12]
	× 80 – 99 per cent	0.08	0.11	0.468	[−0.13, 0.29]
	× 100 per cent	−0.04	0.07	0.539	[−0.19, 0.10]
	DN				
	× ≤79 per cent	0.52	0.09	<0.001	[0.34, 0.71]
	× 80 – 99 per cent	0.44	0.11	<0.001	[0.22, 0.66]
	× 100 per cent	0.69	0.08	<0.001	[0.52, 0.85]
	PBC				
	× ≤79 per cent	0.43	0.07	<0.001	[0.30, 0.56]
	× 80 – 99 per cent	0.30	0.09	0.001	[0.12, 0.48]
	× 100 per cent	0.26	0.06	<0.001	[0.14, 0.38]

A = general attitude, A_R = risk attitude, IN = injunctive norms, DN = descriptive norms, PBC = perceived behavioural control.
LR = linear regression, QR = quantile regression.
[1] n = 359, [2] n = 312 (47 missing values)
Coefficients in the grey shaded cells were significantly different from each other according to an F-test
LR: R^2 = 0.70, adj. R^2 = 0.69.
MLR with age: R^2 = 0.72, adj. R^2 = 0.70.

accommodating both observed and unobserved heterogeneity in the data. This model enables an examination of how different respondent types, delineated by multiple background factors, moderate the relationships between attitude, subjective norm, and PBC, and intentions. While Daxini et al. (2019) pursued a similar methodology, but did not treat background factors as moderators, thereby deviating from the TPB framework. We also recommend making the analysis of heterogeneity in TPB survey data a standard practice in farmer behaviour research.

Despite the refined insights on heterogeneity, our survey methodology is still limited in linking behavioural factors to interventions. Additional longitudinal, experimental, and integrated data approaches could further deepen our understanding of behavioural dynamics, thereby offering policymakers more robust guidance on intervention strategies. Improving the representation of behavioural heterogeneity in theory, data collection and analysis is important to provide policy makers with more detailed and specific guidance on how and when interventions work (Bryan et al., 2021). Examples of more sophisticated approaches include Wang et al. (2023a), who integrated measurements from the stage model (Bamberg, 2013), a social-psychological model based on the TPB, with data from the Dutch Farm Accountancy Data Network (FADN). Currently transitioning into a Farm Sustainability Data Network (FSDN), this platform offers an opportunity to incorporate behavioural factors into harmonized and standardized farm-level data collections. Such integration enables more robust modelling of sustainable crop protection practices, moving beyond simple adoption metrics to assess the potential and realized impacts on pesticide reduction (Finger et al., 2024). Another example is from Torgerson et al. (2024), who employed a research design in which respondents were grouped to investigate the effectiveness of group discussions as a social learning tool and intervention within the TPB framework. These approaches offer scope for better informed future policy recommendations.

In conclusion, we find in line with our previous findings (Bakker et al., 2021) that descriptive norm, i.e. how others are expected to behave, is the main driving factor of intention. Social influencing can be achieved through networks, groups, or communities of practice that facilitate learning and exchange among farmers about ways to reduce pesticide use. However, we also nuanced these findings because the relative impact of attitude and injunctive norm on intention varied across intention levels. The variation was related to differences in age, educational level, and farm income dependency. It may be important for future adoption of more environmentally benign pest management methods with reduced usage of pesticides to account for such variation by developing tailored strategies to reach out effectively to different segments of the farmer population with a variation of strategies. Such strategies could encompass a range of measures, including targeted educational campaigns, incentive programs tailored to specific demographics, and enhanced access to alternative pest control methods.

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CRediT authorship contribution statement

Felix Bianchi: Writing – review & editing, Writing – original draft. **Wopke van der Werf:** Writing – review & editing. **Lieneke Bakker:** Writing – review & editing, Investigation, Data curation. **Jaap Sok:** Writing – original draft, Methodology, Formal analysis, 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.

Data Availability

The authors do not have permission to share data.

Appendix A. Confirmatory factor analysis outcomes

Table A-1
Standardized indicator loading scores (λ's) with the standard error in between brackets, and AVE and CR of each construct after estimation of the final measurement model

Instrumental attitude		Risk attitude		Injunctive norm		Descriptive norm		Perceived behavioural control		Intention	
a_2	0.78 (0.03)	a_4	0.84 (0.01)	in_1	0.88 (0.02)	dn_1	0.88 (0.01)	pbc_1	0.84 (0.03)	i_1	0.90 (0.01)
a_3	0.85 (0.03)			in_2	0.68 (0.03)			pbc_3	0.78 (0.03)		
				in_3	0.75 (0.03)			pbc_4	0.63 (0.04)		
AVE	66.4 %		-		59.5 %		-		57.1 %		-
CR	0.80		-		0.81		-		0.81		-

AVE = Average variance extracted. CR = Convergent reliability.
Model fit: $\chi_2(32) = 48.842$ ($p < 0.029$), RMSEA= 0.038 (0.013 – 0.059), CFI = 0.988, SRMR = 0.027.

Table A-2
Factor inter-correlations matrix (Φ) of the constructs after estimation of the final measurement model

	Instrumental attitude	Risk attitude	Injunctive norm	Descriptive norm	Perceived behavioural control	Intention
Instrumental attitude	1.00					
Risk attitude	0.29**	1.00				
Injunctive norm	0.59**	0.24**	1.00			
Descriptive norm	0.59**	0.33**	0.55**	1.00		
Perceived behavioural control	0.40**	0.25**	0.42**	0.40**	1.00	
Intention	0.59**	0.22*	0.52**	0.65**	0.55**	1.00

* = $p = 0.001$, ** = $p < 0.001$

Appendix B. Structural equation model results

Table B-1
SEM and LR regression model estimates of the effect of attitude, subjective norms and perceived behavioural control on intention to decrease pesticide use.

Regression Type	Predictor	Coefficient (B)	Standard Error (SE)	p-value	95 % Confidence Interval (CI)
SEM					
	A	0.30	0.10	0.003	[0.10, 0.50]
	A_{RISK}	−0.08	0.08	0.333	[−0.24, 0.08]
	IN	0.06	0.08	0.468	[−0.10, 0.21]
	DN	0.44	0.09	<0.001	[0.26, 0.61]
	PBC	0.31	0.07	<0.001	[0.18, 0.43]
LR					
	A	0.32	0.06	<0.001	[0.20, 0.43]
	A_{RISK}	−0.14	0.05	0.005	[−0.23, −0.04]
	IN	−0.00	0.05	0.963	[−0.09, 0.09]
	DN	0.54	0.05	<0.001	[0.44, 0.65]
	PBC	0.34	0.04	<0.001	[0.26, 0.41]

A = general attitude, A_R = risk attitude, IN = injunctive norms, DN = descriptive norms, PBC = perceived behavioural control.
SEM = structural equation modelling, LR = linear regression.
n = 359
SEM: unstandardized results were reported, R^2: 0.54. Model fit: $\chi_2(32) = 48.842$ ($p < 0.029$), RMSEA= 0.038 (0.013 – 0.059), CFI = 0.988, SRMR = 0.027.
LR: $R^2 = 0.70$, adj. $R^2 = 0.69$.

Appendix C. Analysis of which beliefs vary across age groups

We refer to Bakker et al. (2021) for the full descriptions of the belief statements.

Table B-1
For each belief its mean score by age group, number of observations, and the results from an ANOVA test.

Var.	Belief statement	Age (years)				N	F	Prob > F
		≤40	41–50	51–60	≥61			
	Attitudinal							
be1	Less costs and labour	5.5	6.5	5.6	5.4	346	1.15	0.33
be2	Positive for nature and environment	3.1	3.3	2.9	3.5	350	0.40	0.75
be3	Negative influence on crop quality	7.6	7.1	6.7	6.5	350	1.46	0.22
be4	Higher risk of reduced yields	7.4	7.3	7.2	7.0	354	0.16	0.93
be5	More difficult to control pests	7.3	7.0	5.9	6.5	351	1.97	0.12
	Normative (injunctive)							
inm1	Supermarkets and wholesale	4.2	4.5	4.7	4.3	336	0.27	0.85
inm2	Industry and suppliers	0.4	1.0	0.8	0.7	338	0.27	0.85
inm3	Crop advisors	0.3	1.4	1.2	1.8	342	2.19	0.09
inm4	Family or friends	1.2	1.3	1.4	0.7	326	0.80	0.49
inm5	Colleagues with conventional farm	−0.1	0.3	−0.2	−0.4	339	0.70	0.55
inm6	Colleagues with organic farms	1.8	1.9	2.2	3.0	311	2.03	0.11
	Normative (descriptive)							
dni1	Neighbours with organic farms	0.9	1.3	0.8	1.8	276	1.39	0.25
dni2	Neighbours with conventional farms	0.9	0.9	0.5	0.6	348	0.45	0.72
dni3	Members of study groups	1.6	1.5	1.0	1.8	322	1.16	0.33
dni4	Colleague from cooperation	0.9	0.8	0.9	0.9	309	0.03	0.99
	Control							
cp1	More advanced breeding	5.1	5.4	5.5	4.3	343	1.50	0.21
cp2	More technology and mechanisation	4.0	4.3	3.6	3.6	349	0.57	0.64
cp3	Higher prices for produce	7.2	6.8	7.2	6.6	347	0.50	0.68
cp4	Less stringent quality requirements	4.4	3.8	4.1	4.6	341	0.63	0.60
cp5	Changing weather conditions	−3.6	−2.9	−2.0	−1.2	340	3.13	0.03
cp6	Available plant protection products	7.2	7.5	7.2	6.2	348	1.72	0.16
cp7	Reliance on cultivation advice	3.8	3.6	2.9	3.7	347	1.37	0.25
cp8	Longer crop rotation, other varieties	2.3	2.1	2.3	3.5	343	1.54	0.20

Appendix D. Analysis of which beliefs vary across education levels

We refer to Bakker et al. (2021) for the full descriptions of the belief statements.

Table C-1
For each belief its mean score by education level, number of observations, and the results from an ANOVA test.

Var.	Belief statement	Educational level		N	F	Prob > F
		Lower	Higher			
	Attitudinal					
be1	Less costs and labour	5.5	6.1	346	1.35	0.25
be2	Positive for nature and environment	3.2	3.1	350	0.08	0.77
be3	Negative influence on crop quality	6.5	7.4	350	6.34	0.01
be4	Higher risk of reduced yields	6.7	7.8	354	8.19	0.00
be5	More difficult to control pests	6.1	7.1	351	4.65	0.03
	Normative (injunctive)					
inm1	Supermarkets and wholesale	4.3	4.7	336	0.27	0.85
inm2	Industry and suppliers	1.0	0.5	338	1.66	0.20
inm3	Crop advisors	1.4	1.0	342	1.21	0.27
inm4	Family or friends	1.2	1.2	326	0.02	0.88
inm5	Colleagues with conventional farm	0.1	−0.4	339	2.20	0.14
inm6	Colleagues with organic farms	2.3	2.1	311	0.21	0.65
	Normative (descriptive)					
dni1	Neighbours with organic farms	1.5	0.7	276	5.37	0.02
dni2	Neighbours with conventional farms	0.7	0.7	348	0.00	0.99
dni3	Members of study groups	1.4	1.4	322	0.00	0.96
dni4	Colleague from cooperation	1.0	0.8	309	0.33	0.57
	Control					
cp1	More advanced breeding	4.7	5.6	343	3.54	0.06
cp2	More technology and mechanisation	3.8	4.0	349	0.13	0.72
cp3	Higher prices for produce	6.9	7.1	347	0.18	0.67
cp4	Less stringent quality requirements	4.2	4.1	341	0.02	0.89
cp5	Changing weather conditions	−2.1	−2.7	340	1.03	0.31
cp6	Available plant protection products	6.7	7.5	348	4.47	0.04
cp7	Reliance on cultivation advice	3.4	3.4	347	0.01	0.90
cp8	Longer crop rotation, other varieties	2.6	2.4	343	0.08	0.77

Appendix E. Analysis of which beliefs vary across farm-income levels

We refer to Bakker et al. (2021) for the full descriptions of the belief statements.

Table D-1
For each belief its mean score by farm income dependency level, number of observations, and the results from an ANOVA test.

Var.	Belief statement	Dependency on farm income (%)			N	F	Prob > F
		≤79	80 – 99	100			
	Attitudinal						
be1	Less costs and labour	6.1	5.3	5.7	301	0.76	0.47
be2	Positive for nature and environment	3.1	3.5	2.9	303	0.60	0.55
be3	Negative influence on crop quality	6.8	7.4	6.8	304	1.04	0.36
be4	Higher risk of reduced yields	7.0	7.6	7.2	307	0.62	0.54
be5	More difficult to control pests	6.5	7.0	6.0	304	1.66	0.19
	Normative (injunctive)						
inm1	Supermarkets and wholesale	4.3	4.6	4.2	293	0.22	0.80
inm2	Industry and suppliers	0.7	0.9	0.6	296	0.12	0.89
inm3	Crop advisors	1.2	1.8	0.9	298	1.51	0.22
inm4	Family or friends	1.2	1.2	1.0	284	0.13	0.87
inm5	Colleagues with conventional farm	−0.3	0.2	−0.1	295	0.41	0.66
inm6	Colleagues with organic farms	2.3	2.2	2.1	272	0.15	0.86
inm1	Supermarkets and wholesale	4.3	4.6	4.2	293	0.22	0.80
	Normative (descriptive)						
dni1	Neighbours with organic farms	1.7	0.9	0.5	237	3.70	0.03
dni2	Neighbours with conventional farms	0.8	0.3	0.8	303	0.76	0.47
dni3	Members of study groups	1.5	1.1	1.5	278	0.62	0.54
dni4	Colleague from cooperation	0.7	0.7	1.1	269	0.60	0.55
	Control						
cp1	More advanced breeding	4.8	6.0	5.1	299	2.09	0.13
cp2	More technology and mechanisation	4.2	3.7	3.7	305	0.42	0.66
cp3	Higher prices for produce	7.3	6.6	7.0	302	0.59	0.55
cp4	Less stringent quality requirements	4.3	4.0	4.3	298	0.16	0.86
cp5	Changing weather conditions	−2.8	−2.6	−1.8	297	1.49	0.23
cp6	Available plant protection products	6.9	7.5	7.1	302	0.78	0.46
cp7	Reliance on cultivation advice	3.4	3.3	3.6	303	0.19	0.83
cp8	Longer crop rotation, other varieties	2.8	2.7	2.3	298	0.34	0.71

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