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Analysis

Kicking the Habit: What Makes and Breaks Farmers' Intentions to Reduce Pesticide Use?

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ABSTRACT

There is a growing concern in society about the continuing intensive usage of pesticides in farming and its effects on environmental and human health. Insight in the intentions of farmers to reduce pesticide use may help identify pathways towards farming systems with reduced environmental impacts. We used the Reasoned Action Approach to identify which social-psychological constructs determine farmers' intentions to decrease pesticide use. We analysed 681 responses to an online survey to assess which constructs drive intention, and identified which beliefs pose barriers and drive the motivation of farmers to decrease pesticide use. Our results show that the intention to reduce pesticide use is strongly determined by whether other farmers also act. Furthermore, farmers perceive limited capacity and autonomy to reduce pesticide use, and motivations to reduce pesticide use were based on environmental considerations. Finally, decreasing pesticide use was considered risky, but the relative importance of risk attitude was offset by the environmental considerations of farmers. This indicates that farmers need successful examples of how to decrease pesticide use, either via exchange with peer farmers or knowledge provisioning on alternative pest control methods. These insights may be useful to direct policy making to influence farmers' intentions to decrease pesticide use.

1. Introduction

Modern conventional agriculture is dominated by intensive farming systems with highly specialized crop production systems and intensive use of external inputs such as fertilizers and pesticides to enhance and protect yield (Pretty et al., 2018). There are, however, growing concerns in society about the direct and indirect negative effects of pesticides on the environment and health (EASAC, 2015). Pesticides may cause harmful effects on nontarget organisms, such as bees and other beneficial insects, fish, and birds (Lamichhane et al., 2016; Wyckhuys et al., 2019), and many hidden costs are associated with pesticide use, including health care, and monitoring and sanitation of contamination of soils, drinking water, or food. The growing public concern about pesticide use has resulted in societal pressure for a transition towards more ecologically-based pest management. Farmers struggle, however, to change their pest management practices (Lamine, 2011). Integrated Pest Management (IPM) and biological pest control offer the potential to overcome this struggle, but adoption is generally lagging and often not resulting in major reductions in dependency on chemical control. Despite decades of promotion of alternative methods, chemical pest control is therefore still the standard pest management approach in conventional agriculture (Pretty, 2018).

In the Netherlands, pesticide use is relatively high compared to other European countries (Van 't Zelfde et al., 2012). The Dutch directive on sustainable crop protection aims to reduce impacts of pesticides on the environment by 90% in 2023 compared to 2013 (Ministerie van Economische Zaken, 2013), but environmental quality standards in aquatic habitats are still breached (Leendertse et al., 2019; Sporenberg et al., 2019). Here, we aim to provide insight into the intentions of Dutch farmers to decrease their pesticide use, in the context of reducing negative environmental impacts.

While numerous factors influence pest management decisions, there does not seem to be a clear consensus on what the main factors are for farmers to decrease (or not) the use of pesticides and reduce environmental impacts (Lamichhane et al., 2017). Reported barriers include, among others: (i) the absence of non-chemical alternatives (Sporenberg et al., 2019; Tiktak et al., 2019), (ii) lack of knowledge on pesticides and alternatives, (iii) biased information from chemical companies (van den Bosch, 1989; Wilson and Tisdell, 2001), and (iv) an insufficient advisory service on judicious pesticide use (Lamichhane et al., 2016;

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Sherman and Gent, 2014). In addition, Chèze et al. (2020) report that the risk of large production losses due to pests strongly limits farmers' willingness to reduce their pesticide use. Furthermore, economic barriers may arise because of technological lock-in due to past financial investments (Cowan and Gunby, 1996; Wilson and Tisdell, 2001) and market demands for undamaged produce (Skevas and Oude Lansink, 2014). It is also argued that farmers' decision-making is based on non-economic rationale, i.e., farmers' personality traits and ideological motivations (Pedersen et al., 2012; Rodriguez et al., 2009; Siebert et al., 2006).

To understand farmers' decision-making on pesticide use to reduce environmental impacts, we need to identify what factors drive farmers in their decision-making process. In this study, we used the Reasoned Action Approach (RAA), a framework from social psychology, also known as the theory of planned behaviour. The RAA is commonly applied to identify which social-psychological constructs are the most important determinants of intention (Fishbein and Ajzen, 2011). In the field of agricultural research, the RAA has been used to understand intentions to increase soil organic matter (Hijbeek et al., 2018), the uptake of organic farming (Läpple and Kelley, 2013), the engagement in sustainable practices (Lokhorst et al., 2011), disease control in horticulture (Breukers et al., 2012), and prudent use of antimicrobials in cows (Vasquez et al., 2019). We aim to assess the main drivers of farmers' intention to decrease pesticide use to reduce environmental impacts addressing the following questions:

(i) Which social-psychological constructs are the most important determinants of farmers' intention to decrease their pesticide use and reduce environmental impacts?
(ii) Which underlying attitudinal, normative, and control beliefs have the greatest influence on farmers' intentions to decrease their pesticide use and reduce environmental impacts?

We address these questions through the following steps: first, we describe the theoretical framework of the RAA in section 2, then we describe our survey design and statistical analysis in section 3. In section 4 we present the most important constructs driving intention based on a structural equation modelling (SEM) analysis. We then determined for each construct the most influential underlying attitudinal, normative and control beliefs using a Multiple Indicators Multiple Causes (MIMIC) modelling approach. Section 5 provides a discussion on our key findings. We conclude with general conclusions based on our findings.

2. The Theoretical Framework of the Reasoned Action Approach

The RAA is based on the assumption that a person's intention is the best predictor of whether someone will (or will not) perform the behaviour in question, i.e. one's readiness to engage in a particular behaviour (Fishbein, 2008). In this study, we assess four social-psychological constructs that explain behaviour: attitude (A), injunctive norms (Ni), descriptive norms (Nd), and perceived behavioural control (PBC) (Fishbein and Ajzen, 2011; Fig. 1). *Attitude* is the degree to which a person thinks of the behaviour as positive or negative, i.e. 'the willingness' to perform the behaviour. Furthermore, people are influenced by social norms and morals, and in the RAA these perceptions of social pressure are identified as *injunctive norms* (i.e. behaviour that someone expects you to engage in) and *descriptive norms* (i.e. your perception of others' behaviour). Finally, *perceived behavioural control* is the extent to which a person thinks (s)he can perform the behaviour, namely his/her capacity (i.e. ease or difficulty of reducing pesticides) and autonomy (i.e. whether it is up to them) to do so (McEachan et al., 2016).

The social-psychological constructs attitude, injunctive norms, descriptive norms, and perceived behavioural control are latent variables and cannot be assessed directly. They can, however, be assessed in two ways. First, we measured indicator statements that cover different dimensions of behaviour representing each construct ('direct measures'; Fig. 1 - blue box). For example, attitude is assessed through statements that are indicative of why a person holds a certain attitude towards the desired behaviour (Fig. 1, A_1- A_x; Table A1). Secondly, we assessed variables indirectly derived from salient beliefs ('indirect measures'; Fig. 1 – red boxes), following the expectancy-value model (Fishbein and Ajzen, 2011). Indirect measures or belief variables follow from individuals' personal beliefs or expectations about performing specific behaviour, multiplied by an (e)valuation of these beliefs in terms of importance (Fishbein, 2008). For example, attitudinal belief variables (Fig. 1; *be*) were assessed with a belief statement on how likely something would occur ('belief strength' (*b*)), followed by an evaluation of how important that something is towards intentions to decrease pesticide use to reduce environmental impact ('outcome evaluation' (*e*)) (Table A2) (Fishbein and Ajzen, 2011).

3. Methods

3.1. Survey Design and Sample

To elicit and measure the most commonly held attitudinal, normative, and control beliefs, we first conducted a pilot study. This pilot study consisted of a series of semi-structured interviews held with eight arable farmers in October and November 2018. Interviewees were given a description of the behaviour and were asked a series of questions designed to identify these beliefs (Fishbein and Ajzen, 2011). After the eighth interview, we reached a saturation point, with no new beliefs being mentioned. The answers given by the interviewees were used in the formulation of questions in the survey to assess why people hold certain attitudes, subjective norms, and perceptions of control.

The survey consisted of three sections. First, we assessed each construct using one to four statements (Table A1), following *"Decreasing my use of environmentally harmful pesticides within two years is …"* (Fishbein and Ajzen, 2011). Respondents were asked to rate a total of fifteen statements to measure all constructs. These statements were 'direct measures' as discussed in the previous section. Each statement was rated using a five-point Likert-like scale from 1 to 5. A three was considered a neutral response; higher values were considered agreement, and lower values disagreement. Subsequently, respondents were asked to rank statements on underlying beliefs ('indirect measures') for each of the constructs A, Ni, Nd, and PBC (Table A2). For each belief statement farmers were asked to rate a probability on a 5-point Likert scale from 'not likely' (1) to 'likely' (5), i.e. the belief strength. Then farmers were asked to evaluate these belief statements from 'plays no role' (-2) to 'plays a role' ($+2$), i.e. the valuation. A Likert score of three and zero, for belief strength and valuation, respectively, was considered a neutral response; higher values were considered agreement, and lower values disagreement. In our analysis, we used belief variables ('indirect measures') with a range from -10 to $+10$. These variables are based on multiplying the belief strength with the corresponding outcome evaluation, following the expectancy-value model. For ease of interpretation, here we report for both direct and indirect measures rescaled values on a -2 to $+2$ range. To do so, we subtracted -3 for each direct measure indicator, and divided indirect measures ('belief variables') by five. Finally, several questions regarding demographic and farm characteristics were asked: respondents' age, gender, farm size (ha), household income (%), type of farm (organic or conventional), education, crop rotation, main crop, landscape information (postal code and landscape description) and pest pressure, as well as which information sources farmers used to inform themselves on crop protection.

To reach the largest number of Dutch farmers possible, we collaborated with "Geelen consultancy" (https://www.geelen-consultancy.nl/) to distribute an e-mail invitation to complete an online survey to ± 7500 farmers in the Netherlands. This sample entailed approximately two-thirds of the Dutch arable farmer population consisting of

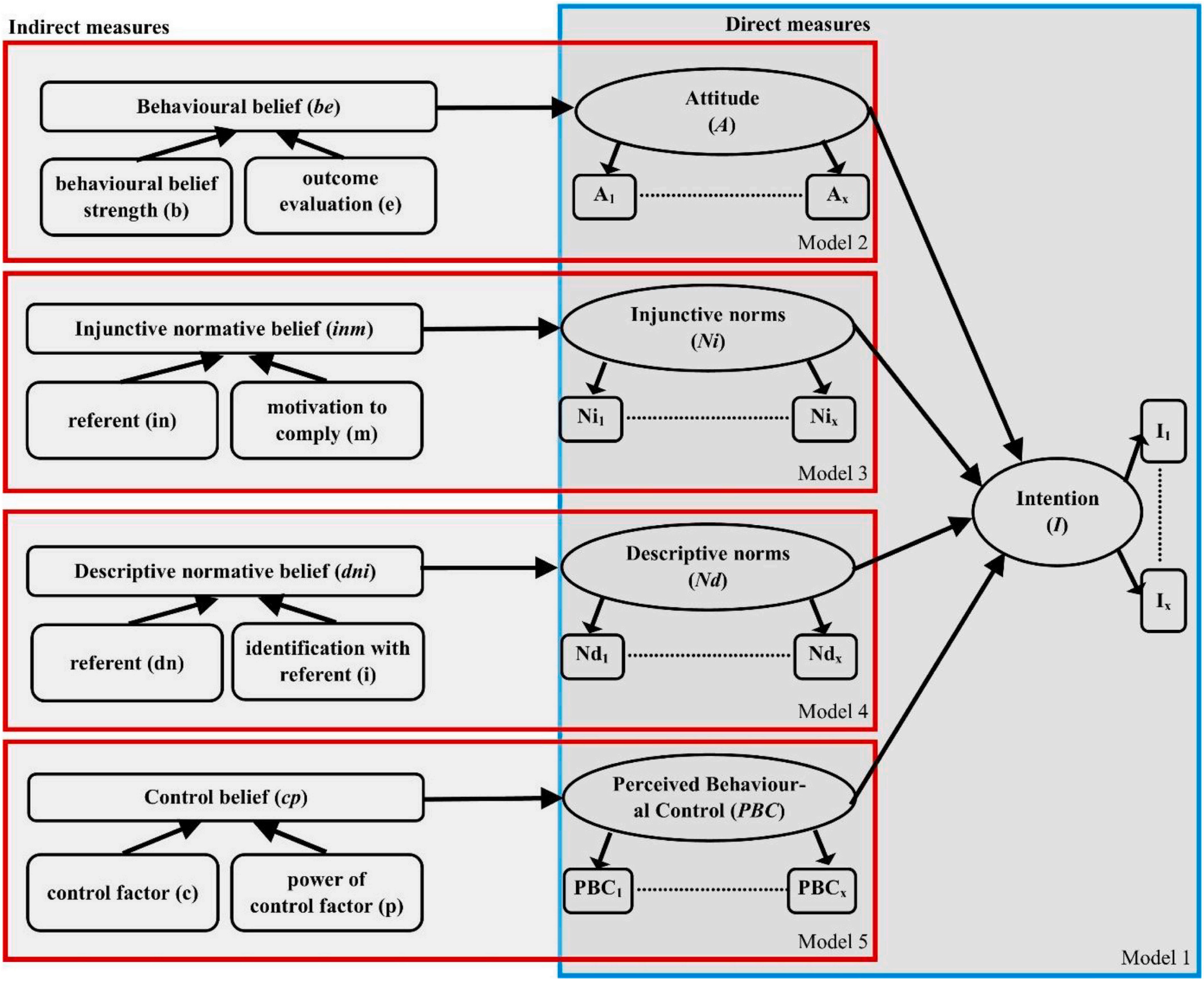

Fig. 1. Schematic overview of the Reasoned Action Approach (RAA) (Fishbein and Ajzen, 2011). In Model 1 (blue box) we identify which social-psychological constructs (ellipses) are most important towards intentions to decrease pesticide use and reduce environmental impact. Constructs are latent variables, and we measured 'direct measures' (rounded rectangles) as indicators representing each construct. Models 2–5 (red boxes) determine the most influential underlying belief variables (rounded rectangles) of each construct. Belief variables are composite values based on (i) personal beliefs or expectations about performing specific behaviour (belief strength/ referent/control factor), and (ii) (e)valuation of the importance of the belief/referent/control factor. Referents are persons that influence an individual's social norms. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

8709 arable farmers, 959 flower bulb growers, 1318 vegetable growers and 1498 fruit growers in 2019 (CBS, 2020) (Table 1). Participation was voluntary, and as an incentive to participate, respondents could win one of the 50 gift vouchers of €20. The survey was available online from February 20th, 2019 till May 23rd, 2019. We allowed farmers to answer questions with 'don't know' or 'not applicable' to reduce errors. Selection criteria for including responses in the analysis were: (i) respondents should be farmers from the arable, fruit, vegetable or flower bulb sector, and (ii) respondents should currently use pesticides on their farm. This resulted in 681 out of 1190 responses being included for analysis; 448 respondents were arable farmers, 67 flower bulb growers, 122 fruit growers and 44 were vegetable growers (Table 1).

The average age of the respondents was 51 ± 11 years, and farm size ranged from 1.6 ha to 650 ha. For most respondents (62%) the farm provided more than 75% of the family income. Most respondents were men (92%), and had completed either secondary professional education (47%) or higher education (34%) (Table 1). Our sample provides a reasonable reflection of the Dutch farmer population regarding age, gender, income, farm type and farm size (Table 1). In the Netherlands, all farmers that use pesticides have to comply with national regulations and need to obtain a spraying licence (LNV, 2020). Therefore, we assumed that all respondents were knowledgeable on impacts of pesticides on the environment, and that variation in knowledge level was limited.

3.2. Statistical Analysis

We estimated five models following the procedure as described by Sok et al. (2015), and Vasquez et al. (2019) (Fig. 1). First, in Model 1 we determined the most important constructs driving intention using SEM (Fig. 1; blue box). In Models 2–5 we used a MIMIC modelling approach to determine the most influential underlying beliefs of each construct (Fig. 1; red boxes).

We used McDonalds' coefficient omega (ω) and average variance extracted (AVE) to determine the internal consistency of variables used for validating psychometric tests. AVE values > 0.5 and ω > 0.7 are

Table 1
Overview of farm and farmer characteristics of respondents (n = 681) compared to data from the Netherlands (CBS, 2020; 2016).

		Survey sample	%	Netherlands (%)
Income from farm[a]	< 25%	30	4	7
	25–75%	115	17	16
	> 75%	425	62	75
	No answer	111	16	2
Gender[a]	Male	628	92	95
	Female	28	4	5
	No answer	25	4	–
Education[a]	None	1	0	0
	Primary school	37	5	4
	High school diploma	71	10	22
	Sec. prof. education	317	47	60
	Higher education	232	34	12
	No answer	23	3	2
Farm type[b]	Arable	448	66	70
	Flower bulb	67	10	8
	Vegetable	44	7	11
	Fruit	122	18	12

[a] Netherlands data from 2016.
[b] Netherlands data from 2019.

considered to indicate reliability (Padilla and Divers, 2016). Overall model fit was evaluated using criteria for good fit: Comparative Fit Index (CFI > 0.9), Tucker-Lewis fit Index (TLI > 0.9), root mean square error of approximation (RMSEA < 0.08), and root mean square residual (SRMR < 0.1) (Brown, 2015; Parry, 2017). Mardia's multivariate skewness (b1 = 27.21, X^2 (1140) = 3088.65, p = 0.00) and kurtosis (b2 = 433.38, z2 = 35.68, p = 0.00) tests indicated that normality assumptions were not met. Therefore, we used the Satorra-Bentler method, a robust ML estimator with robust standard errors and a Satorra-Bentler scaled test statistic (Brown, 2015; Cain et al., 2017; Kline, 2005; Satorra and Bentler, 1994). In our analysis, we refer to direct measures as 'indicators' and indirect measures as 'variables'.

3.2.1. Model 1 – Direct Measures

For Model 1 we used a two-step approach to estimate which constructs of behaviour are the main drivers of intentions to reduce pesticide use (Fig. 1; blue box). First, we estimated a measurement model in which we a priori assigned indicators to constructs. These indicators were A1-A4, Ni1-Ni3, Nd1, PBC1-PBC4, and I1-I3 (Table A1). Using Confirmatory Factor Analysis (CFA), we assessed model fit and evaluated which indicators were representative of each construct. The measurement model was revised by deleting indicators that had very low values of factor loading and squared multiple correlation (R^2). In addition, we removed indicators that attempted to load on more than one construct, as indicated by high modification indexes (Brown, 2015). This procedure resulted in the removal of indicators A1, PBC2, I2, and I3. The results of the measurement model further showed that indicator A4 ('risky') differed from the other indicators for attitude ('necessary' and 'important'). We used these low correlations as a justification for the separation of the main A construct in two separate constructs: attitude (A) and risk attitude ('A_r'). Descriptive statistics for each indicator and the correlation matrix are presented in Table B1, while the overall fit statistics of the original and revised measurement model (Model 1), as well as reliability measures (ω and AVE) for each construct are reported in Table B2.

Second, we estimated a structural model based on the re-specified measurement model. The structural model was used to determine the relative importance of each construct (A, A_r, Ni, Nd, and PBC) towards intention (I) (Fig. 2). As a robustness check, we assessed differences between farmer types by conducting a multigroup analysis. We compared the free structural model and a constrained model with fixed intercepts and path coefficients to assess whether all coefficients were significantly different across groups or not. Comparing the free and constrained multigroup model (X^2 (30) = 32.936, p = 0.33) indicated that the coefficients did not significantly differ between groups, and therefore we kept the pooled data for further analyses. We estimated different model specifications to assess the impact of multicollinearity in the final model with all constructs included (Table 2).

3.2.2. Models 2–5- Indirect Measures

The most relevant beliefs, referents (i.e. persons that influence an individual's social norms), and factors were analysed using MIMIC modelling (Fig. 1 – red boxes). The results of Models 2–5 provide insight into which underlying beliefs pose barriers and drive the motivation of farmers to decrease pesticide use. In Model 2 we estimated which attitudinal beliefs (be1-be5; Table A2) were most important determining A and A_r. Model 3 estimated the most important referents (inm1-inm6; Table A2) for injunctive norms (Ni), and in Model 4 we estimated the most important referents for descriptive norms (Nd) (dni1-dni4; Table A2). Model 5 estimated what underlying control factors (cp1 – cp8; Table A2) were most important for PBC. Records with missing data were discarded. This resulted in 630 observations for A, 563 observations for Ni, 510 observations for Nd, and 570 observations for PBC. Variance inflation factors (VIF) indicated that there was no variable redundancy (VIF < 5). Therefore, all belief variables were kept for the analysis. Final MIMIC models were obtained after the stepwise deletion of non-significant variables (Diamantopoulos, 2011).

All analyses were conducted in R (R Development Core Team, 2019) with the lavaan-package for SEM and MIMIC models (Rosseel, 2012). Figures were created using the semPlot package (Epskamp, 2015).

4. Results

4.1. Direct Measures

4.1.1. Descriptive Statistics

Mean response values for indicators A1-A3 ranged from −0.45 to 0.39 (on a scale from −2 to +2). The centering of scores around zero indicates that respondents do not perceive the behaviour of decreasing pesticide use as either 'good' or 'bad'. Interestingly, the mean value for the indicator A4 - 'risk' - was valued negatively (−1.11), which implies that farmers perceive decreasing pesticide use as risky. Farmers' injunctive norms (Ni) - what others expected from the farmer - were neutral ranging from −0.33 to 0.08, indicating that important people from the sector, friends or family did not play a role in pesticide use decision-making. Descriptive norms (Nd) were assessed with a statement on respondents' expectations of whether colleague-farmers would reduce their pesticide usage. The mean valuation of this statement was −0.2, which can be considered as a neutral opinion on whether other farmers would decrease their pesticide use. Mean rank scores for perceived control indicators PBC1-PBC4 ranged from −0.62 to −0.21, indicating that farmers have a slightly negative perception about their ability to decrease pesticide use. Finally, respondents' intention to decrease pesticide use was neutral to moderately positive; 0 to 0.24. In other words, on average respondents showed a slight intention to decrease their pesticide use.

4.1.2. Model 1: Identifying the Main Determinants of Intention

The fitted structural model of significant drivers of intention to decrease pesticide use is presented in Fig. 2: attitude, injunctive norms, descriptive norms, and perceived behavioural control all emerged as significant predictors of intentions. Total explained variance in intention (I) was 65%, with Nd being the most important determinant, followed closely by PBC, A, and Ni (Fig. 2; Table 2). Thus, the intention to decrease pesticide use is related to the social pressure respondents feel from expectations on what other farmers will do (β_{Nd} = 0.34). Furthermore, respondents' feelings of perceived control affect intentions to

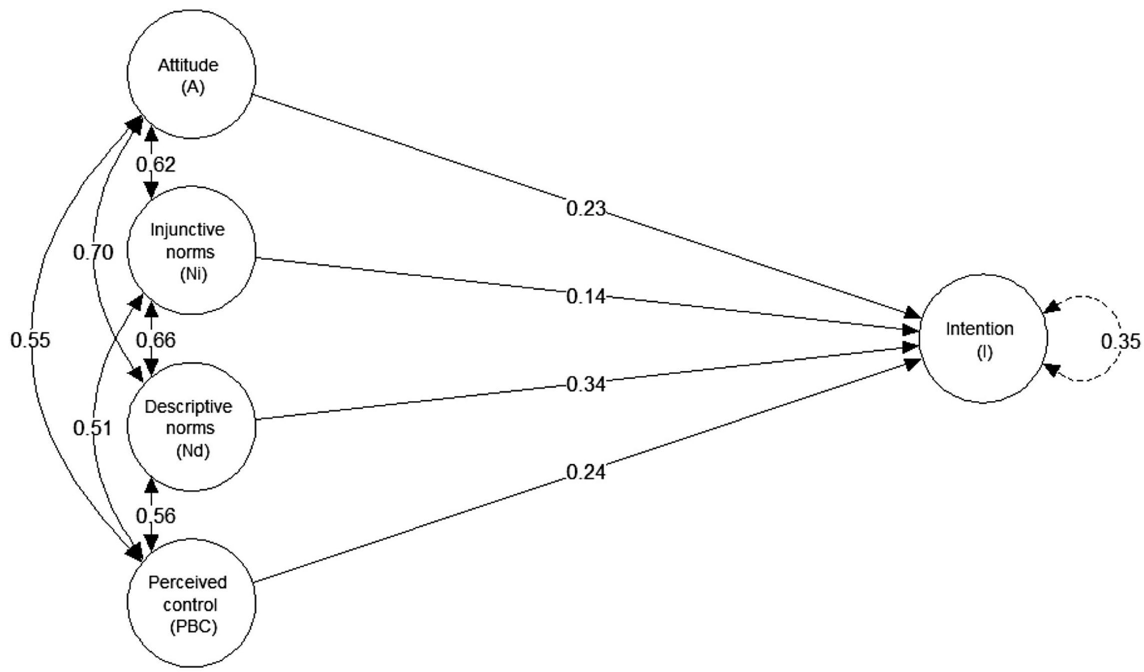

Fig. 2. Final structural model of intention to decrease pesticide use to reduce environmental impacts (Model 1 in Fig. 1). Circles represent constructs, straight solid arrows represent regression coefficients, the dashed arrow indicates an error term, and double-headed solid arrows represent correlations. All estimates have p-values < 0.05. Overall fit statistics were $X^2(27) = 47.704$ ($p = 0.008$), CFI = 0.993, TLI = 0.988, RMSEA = 0.037 (0.019–0.054) and SRMR = 0.021.

Table 2
Standardized factor loadings in different structural model specifications with intention (I) as the dependent variable (Model 1). Standardized factor loadings can be interpreted as regression coefficients and are given for each construct inserted in the model.

		Beta-estimates of:					
		1	2	3	4	5	
Model 1	Includes	Attitude (A)	Risk attitude (A_r)	Subjective Injunctive norms (Ni)	Subjective descriptive norms (Nd)	Perceived Behavioural Control (PBC)	R^2
A	1	0.69*					0.47
B	2		0.35*				0.12
C	3			0.63*			0.40
D	4				0.73*		0.54
E	5					0.63*	0.40
F	1,2	0.65*	0.09				0.48
G	3, 4			0.26*	0.56*		0.57
H	1, 2, 3, 4	0.29*	0.03	0.18*	0.40*		0.61
I	1,3,4,5	0.23*		0.14*	0.34*	0.24*	0.65
J	1, 2, 3, 4, 5	0.23*	0.00	0.14*	0.34*	0.24*	0.65

* p-value < 0.05.
R^2-values reflect the explained variance in I.

decrease pesticide use ($\beta_{PBC} = 0.24$), as do attitudinal considerations ($\beta_A = 0.23$). Moreover, considerations on what a respondent ought to do (injunctive norms) ($\beta_{Ni} = 0.14$) can be considered a driver of intention.

Univariate analysis indicated that all constructs, including risk attitude, were significant determinants of intention (Table 2). Risk attitude (A_r) as a single predictor explained intention (12%), but was not significant when other constructs were added to the model. This suggests that the relative importance of risk attitude on intentions to decrease pesticide use is offset by the other social-psychological constructs.

4.2. Indirect Measures

4.2.1. Descriptive Statistics

When comparing the five attitudinal beliefs, the highest mean rank score was given to 'Loss of yields' (be4) (1.49 on a scale from −2 to +2). This indicates that respondents expected that yields may decrease if they would decrease their pesticide use, and that they consider this very important. This belief had the highest correlation with risk attitude, suggesting that respondents' attitudinal risk considerations are mostly related to beliefs on yield losses (Table 3). The second highest mean rank score was given to 'Crop quality' (be3), followed by 'Pest control' (be5) (1.43 and 1.37, respectively). Both beliefs have negative correlations with attitude and risk attitude, suggesting that farmers believe that a decrease of pesticide use would make pests more difficult to control, and would reduce crop quality and yield as a result. 'Nature & environment' (be2) had a mean rank score of 0.64 and had the strongest correlation with attitude. This implies that respondents belief that a reduction in pesticide use is likely to be positive for nature and environment, and they think it is important to reduce their pesticide use for the environment. We expected that costs and labour would influence attitude, but this was not shown in the analysis. 'Costs & labour' (be1) had the lowest mean rank score (0.42), indicating that respondents' are

Table 3
Descriptive statistics of indirect measures for attitude (A) and risk attitude (A_r).

Variable	Attitudinal belief statement	CorrA[a]	CorrA$_r$[a]	Mean (SD)[b]	N
be1	I will have less costs and labour	0.05	0.14**	0.42 (0.45)	657
be2	This will be positive for nature and environment	0.46**	0.21**	0.64 (0.82)	659
be3	This has a negative influence on my crop quality	−0.17**	−0.35**	1.43 (0.68)	662
be4	I have a higher risk of reduced yields	−0.21**	−0.38**	1.49 (0.68)	669
be5	It will be more difficult to control pests	−0.13**	−0.20**	1.37 (0.78)	663

** p-value < 0.01.
[a] CorrA and CorrA$_r$ are correlations with the average of variables representing the constructs attitude (A) and risk attitude (A_r).
[b] Variables range from −2 to +2, and are multiplicative composites of two question types; a belief strength valuation (unlikely-likely) and an outcome evaluation ((not) important) (see Table A2).

not sure if it is likely that decreasing their pesticide use would result in a change in costs and labour. Besides be2, the attitudinal belief variables were weakly correlated with attitude, while they had a strong correlation with risk attitude. This indicates that the underlying attitudinal belief variables in this model are more formative of risk attitude, than farmers' willingness to decrease pesticides. However, as shown in the previous section, risk attitude has a weaker influence on intentions to decrease pesticide use than attitude. In addition, attitude (A) was mainly formed by beliefs on nature and the environment.

We assessed six normative injunctive referents, of which ‘Supermarkets & wholesale’ was the most important referent with the highest mean rank score (0.95; Table 4). This suggests that farmers consider supermarkets to be in favour of a decrease in pesticide use, and that this opinion is rather important for respondents. While ‘Colleagues with organic farms’ came second with a mean rank score of 0.45, this referent had the highest percentage of ‘not applicable’ ticks (11.6%), i.e. more than 10% of the respondents did not know organic farmers that would expect them to decrease their pesticide use. The mean rank scores of the other four referents were centred around zero (−0.04 to 0.25), implying that respondents perceive a neutral social norm from these important persons regarding their intentions to reduce their pesticide use.

Out of four descriptive normative referents, ‘Members of study groups’ had the highest mean rank score of 0.24 (Table 5), but all four referents were scored within a similar range. This implies that respondents feel little social pressure from descriptive referents, and that they do not know whether their neighbours or colleagues will decrease their pesticide use. ‘Neighbours with organic farms’ had the highest number of ‘not applicable’ ticks, indicating that more than 20% of the respondents did not know organic farmers. Moreover, the mean rank score for this referent was 0.21 and had the lowest correlation with descriptive norms. These results suggest that most respondents have neutral to slightly positive opinions in associating themselves with

Table 4
Descriptive statistics of indirect measures for injunctive norms (Ni).

Variable	Referent	Corr[a]	Mean (SD)[b]	N	%NA[c]
inm1	Supermarkets & wholesale	0.37**	0.95 (0.86)	635	6.75
inm2	Industry & suppliers	0.24**	0.16 (0.70)	638	6.31
inm3	Crop advisors	0.33**	0.25 (0.70)	646	5.14
inm4	Family or friends	0.40**	0.23 (0.64)	620	8.96
inm5	Colleagues with conventional farms	0.29**	−0.04 (0.67)	641	5.87
inm6	Colleagues with organic farms	0.30**	0.45 (0.64)	602	11.6

** p-value < 0.01.
[a] Corr are correlations of each variable with the average of the direct measures of the construct Ni.
[b] Variables range from −2 to +2 and are multiplicative composites of two question types; a normative belief strength valuation ((dis)approve) and motivation to comply ((not) important) (see Table A2).
[c] %NA refers to the percentage of respondents answering with ‘not applicable’.

Table 5
Descriptive statistics of indirect measures for descriptive norms (Nd).

Variable	Referent	Corr[a]	Mean (SD)[b]	N	%NA[c]
dni1	Neighbours with organic farms	0.29**	0.21 (0.64)	533	21.73
dni2	Neighbours with conventional farms	0.47**	0.11 (0.60)	653	4.11
dni3	Members of study groups	0.50**	0.24 (0.64)	617	9.4
dni4	Colleague from cooperation	0.45**	0.19 (0.61)	589	13.51

** p-value < 0.01.
[a] Corr are correlations of each variable with the average of the direct measures of the construct Nd.
[b] Variables range from −2 to +2 and are multiplicative composites of two question types; a normative belief strength valuation ((un)likely) and identification with referent ((not) important) (see Table A2).
[c] %NA refers to the percentage of respondents answering with ‘not applicable’.

organic farmers on this topic, and they consider it likely that organic farmers will reduce their pesticide use. The other three descriptive normative referents have strong correlations with descriptive norms, indicating that respondents do identify with these referents.

We identified eight control factors (Table 6) of which the highest mean rank score was given to ‘Higher crop prices’ (*cp3*) and ‘Greater choice in plant protection products’ (*cp6*) (1.38 and 1.35, respectively). Respondents thought it important that they should get higher crop prices and availability of more choice in plant protection products to make it easier to decide to reduce their pesticide use. However, the control factor ‘Higher crop prices’ is not correlated with PBC, implying that this is not a determining factor for the respondents' intention to decrease pesticides. Other control factors that had low correlations are ‘Advanced breeding’ (cp1) and ‘Quality requirements’ (cp4), which suggests that these factors are not perceived as possible barriers regarding decreasing pesticide use. ‘Weather conditions’ has a negative mean rank score of −0.50. This implies that farmers do not think they could rely on favourable weather conditions, and they do expect that changing weather conditions will make it more difficult to decrease their pesticide use.

4.2.2. Identifying Main Beliefs, Referents and Factors

4.2.2.1. Model 2: Identifying Main Attitudinal Beliefs. The attitudinal belief variables explained 31% of the variance in A, and 34% of the variance in A_r (Fig. 3; Table 7). The variables ‘Pest control’ (be5), ‘Crop quality’ (be3), and ‘Costs & labour’ (be1) were not significant for A. Only ‘Pest control’ (be5) was not significant for A_r and was removed from the final model. ‘Nature & environment’ (be2) was the most important belief for attitude, and ‘Loss of yields’ (be4) was the second most important belief. In contrast, ‘Loss of yields’ (be4) was the most important belief for A_r, followed by ‘Nature and environment’ (be2). ‘Loss of yields’ has a strong negative coefficient towards A_r ($\gamma_{be4} = -0.36$), indicating that the risk of reduced yields had a strong influence on risk attitude. ‘Crop quality’ (be3) and ‘Costs &

Table 6
Descriptive statistics of indirect measures for perceived behavioural control (PBC).

Variable	Control belief statement	Corr[a]	Mean (SD)[b]	N
cp1	I would be required to use more advanced breeding	0.04	0.97 (0.86)	629
cp2	I would be required to use more precise technology and mechanisation	0.21**	0.78 (0.92)	661
cp3	I should receive a higher price for my product	0.07	1.38 (0.86)	659
cp4	the quality requirements on my products should be less stringent.	−0.06	0.88 (0.87)	646
cp5	I would rely on favourable weather conditions	0.14**	−0.50 (1.02)	640
cp6	I would rely on a greater choice in plant protection products	−0.11**	1.35 (0.82)	665
cp7	I would rely on cultivation advice	0.15**	0.67 (0.79)	660
cp8	I would have to consider a longer crop rotation and other crop varieties	0.20**	0.49 (0.96)	622

** p-value < 0.01.
[a] Corr are correlations of each variable with the average of the direct measures of the construct perceived behavioural control (PBC).
[b] Variables range from −2 to +2 and are multiplicative composites of two question types; a control belief strength valuation ((un)likely) and power of control (difficult-easy) (see Table A2).

labour' (be1) were also significant variables but had a weak effect on A_r. In summary, most attitudinal beliefs explained the risk attitude of the respondents, and the indicator 'Nature & environment' most strongly influenced the attitude of respondents (Fig. 3).

4.2.2.2. Model 3: Identifying Main Injunctive Referents. The injunctive referents explained 29% of the variance in Ni (Fig. C1; Table 7). We removed 'Industry & suppliers' (inm2) and 'Colleagues with conventional farms' (inm5) due to non-significance. 'Family and friends' (inm4) were the most important referents, closely followed by 'Supermarkets' (inm1). In addition, 'Crop advisors' (inm3) and 'Colleagues with organic farms' (inm6) were influential normative injunctive referents. Thus, the most influential referents that exert social pressure on respondents were relatives, business relations, and colleagues that already have set an example of less or no pesticide use.

4.2.2.3. Model 4: Identifying Main Descriptive Referents. The descriptive referents explained 42% of the variance in Nd (Fig. C2; Table 7). The referent 'Colleagues from cooperation' (dni4) was removed due to non-significance. The referents with the strongest influence on descriptive norms were 'Neighbouring colleagues from conventional farms' (dni2) and 'Members of study groups' (dni3) (γ_{dni2} = 0.32 and γ_{dni3} = 0.30, respectively). This indicates that the opinion of people who farmers see as their equals could be important for decision-making on reduced pesticide use.

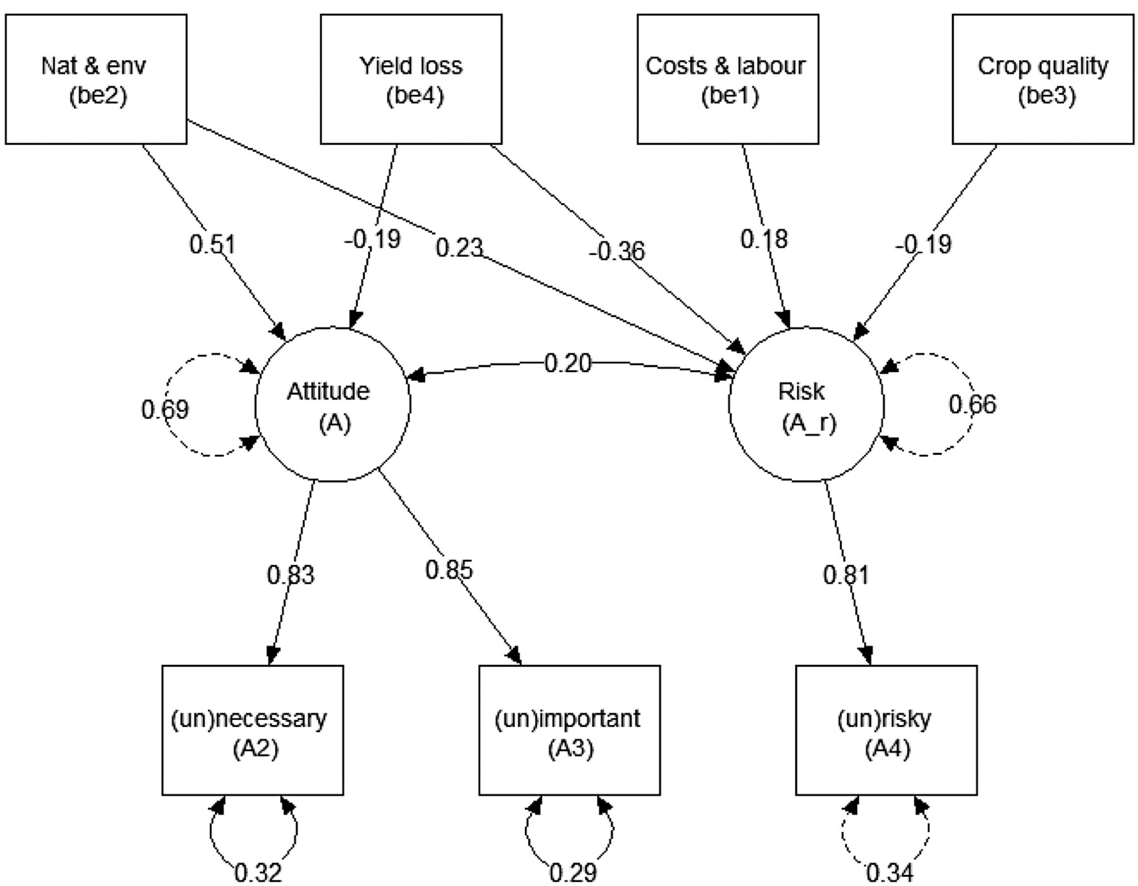

Fig. 3. Final structural diagram of MIMIC model to determine the most important underlying beliefs of attitude (A) and risk attitude (A_r) (Fig. 1; Model 2). Circles represent constructs, squares are measured indicators (A_n) and variables (be_n), straight solid arrows represent regression coefficients, dashed arrows are measurements errors, and double-headed solid arrows represent correlation. All estimates are significant ($p < 0.05$). Overall fit statistics: $X^2(6) = 5.61, p = 0.47$, CFI = 1, TLI = 1, RMSEA = 0 (0–0.052), SRMR = 0.01.

Table 7
Estimates of the final MIMIC models for the constructs attitude (A), risk attitude (A_r), injunctive norms (Ni), descriptive norms (Nd), and perceived behavioural control (PBC). Regression coefficients (γ-values) show the relative importance of each belief variable (e.g. be1) on the construct (e.g. A). Four MIMIC models are shown; be1-be5 for A & A_r (Model 2 in Fig. 1); inm1-inm6 for Ni (Model 3 in Fig. 1); dni1-dni4 for Nd (Model 4 in Fig. 1); and cp1-cp8 for PBC (Model 5 in Fig. 1).

		Indicator	A	A_r	Ni	Nd	PBC	p-value
Attitude & Risk attitude	*Costs & labour*	be1		0.18				0.00
	Nature & environment	be2	0.51	0.23				0.00
	Crop quality	be3		−0.19				0.00
	Loss of yields	be4	−0.19	−0.36				0.00
	Pest control	be5						n.s.
Injunctive norms	*Supermarkets & wholesale*	inm1			0.22			0.00
	Industry & suppliers	inm2						n.s.
	Crop advisor	inm3			0.15			0.00
	Family or friends	inm4			0.24			0.00
	Colleagues with conventional farms	inm5						n.s.
	Colleagues with organic farms	inm6			0.16			0.00
Descriptive norms	*Neighbours with organic farms*	dni1				0.17		0.00
	Neighbours with conventional farms	dni2				0.32		0.00
	Members of study groups	dni3				0.30		0.00
	Colleague from cooperation	dni4						n.s.
Perceived Behavioural Control	*More advanced breeding*	cp1						n.s.
	Precise technology and mechanisation	cp2					0.25	0.00
	Higher crop prices	cp3						n.s.
	Less stringent quality requirements	cp4					−0.13	0.01
	Weather conditions	cp5					0.11	0.02
	Greater choice in crop protection products	cp6					−0.17	0.00
	Cultivation advice	cp7					0.11	0.03
	Longer crop rotation and other crop varieties	cp8					0.12	0.02
		R^2	0.31	0.34	0.29	0.42	0.15	
		N	630		563	510	681	
		X^2	5.61		20.95	1.93	14.78	
		df	6.00		8.00	3.00	12.00	
		p-value X^2	0.47		0.01	0.59	0.25	
		CFI	1.00		0.98	1.00	1.00	
		TLI	1.00		0.96	1.01	0.99	
		RMSEA	0.00		0.06	0.00	0.02	
		SRMR	0.01		0.02	0.01	0.01	

R^2 = explained variance of construct, χ^2 = Chi-square; df = degrees of freedom; CFI = Bentler's comparative fit index; TLI = Tucker-Lewis fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

4.2.2.4. Model 5: Identifying Main Control Factors. The eight control factors explained 16% variance in PBC (Fig. C3; Table 7). We removed ‘More advanced breeding’ (cp1) and ‘Higher crop prices’ (cp3) due to non-significance. Important barriers were two control factors underlying a farmers' perceived capability; ‘More precise technology & mechanisation’ (cp2) and ‘Greater choice in plant protection products’ (cp6). The latter had a negative coefficient ($\gamma_{cp6} = -0.17$), indicating that less choice in plant protection products would negatively influence the farmers' perceived capability to decrease pesticide use. Factors associated with external conditions (e.g., ‘Weather conditions’, ‘Advanced breeding’, and ‘Crop prices’) had little to no influence on a farmers' perceived ability to decrease pesticide use.

5. Discussion

While there is a growing societal demand to reduce the environmental impacts of pesticides, farmers are struggling to become less dependent on pesticides for crop protection. To identify pathways towards reduced environmental impacts of pesticides, we aimed to understand which social-psychological constructs influence farmers' decisions on pesticide use (to reduce environmental impacts). We used a quantitative approach based on the Reasoned Action Approach to estimate the relative influence of different social-psychological constructs on farmers' intentions to reduce pesticide use. Descriptive norms, perceived behavioural control, attitude, and injunctive norms all emerged as significant predictors of intention. We discuss four key findings. First, the intention of farmers to reduce pesticide use is strongly determined by whether other farmers also act, i.e. the perceptions on behaviour of others. Second, farmers felt little sense of control and perceive limited capacity and autonomy to reduce pesticide use. Third, farmers' motivations to reduce pesticide use were based on moral considerations regarding what is good for nature and the environment. Finally, decreasing pesticide use was considered risky, but the relative importance of risk attitude was offset by the environmental considerations of farmers.

First, farmers' intentions to decrease pesticide use were driven by descriptive norms, i.e., expectations on other farmers' behaviour. The most important referents were peers like conventional neighbouring farmers and members from study groups, i.e., those individuals who farmers view as like-minded (i.e., shared values or experiences) or credible experts (Perry and Davenport, 2020; Sok et al., 2015). These results confirm the findings of other studies about the importance of support by neighbours towards the implementation of new management strategies (Brewer and Goodell, 2012; Parsa et al., 2014; Stallman and James, 2015). For example, if a neighbour had a positive experience with conservation practice (e.g. reduced tillage), this served as a positive model for farmers who still had to apply the measure (Ahnström et al., 2009; Perry and Davenport, 2020). Farmers typically do not make radical changes in their decision-making, but rather implement new practices gradually (Chantre and Cardona, 2014). Thus, observing positive outcomes of reduced pesticide use on the environment can serve to increase intentions to decrease pesticide use. This stresses the importance of network and neighbourhood connections in influencing farmers' decision-making on pest management. For example, farmers believed that if they worked together with their neighbour, they could more effectively manage pests (Stallman and James, 2015). Indeed, farmers' decisions on IPM play out at a larger scale than their individual farms and can therefore benefit from a landscape approach (Brewer and Goodell, 2012; Parsa et al., 2014).

This highlights the importance of collective action, and future strategies may build on the importance of knowledge and communication transfer to enhance these social interactions. Trust is a key element in behaviour change (Green et al., 2020), and needs to be central to supporting discussions on norms and values. This could be addressed through the facilitation of focus groups (Perry and Davenport, 2020), and discussions with neighbours on the positive outcomes of reduced pesticide use to enhance farmers' intentions.

Secondly, the main perceived barriers to decrease pesticide use were capacity related. This is in agreement with other studies, e.g. Sporenberg et al. (2019) and Hammond Wagner et al., 2016. These studies also indicated that the availability of crop protection products was one of the main barriers that farmers perceive in changing their decision-making on pest management. Currently, farmers consider pesticides to be the most effective method to manage pests (Atreya et al., 2011; Skevas et al., 2012). Thus, a reduction in choice availability of synthetic pesticides translates in reduced confidence in the ability to effectively control pests. This emphasizes that farmers perceive a dependency on pesticides to manage pests. Yet, our study also shows that external control factors that include non-chemical alternatives, e.g. 'more precise technology and machinery', 'expert advice' and a 'longer crop rotation and other crop varieties', were perceived as factors that could facilitate farmers' sense of control, and positively influence intentions to decrease pesticide use. Furthermore, our measured control beliefs only explained 16% of the variance of perceived behavioural control, and were mainly capacity-related. This shows that we missed out on control factors that are indicative of farmers' sense of autonomy. This is important to note, as previous studies have found that knowledge on the effects of pesticide use on the environment and personal health is an important factor determining actual use of pesticides (Bagheri et al., 2019; Calliera et al., 2013; Damalas and Koutroubas, 2014; Khan and Damalas, 2015). To strengthen the sense of autonomy it is important to support farmers in making strategic and tactical pest management decisions, e.g. through expert advice, education and knowledge transfer (Sherman and Gent, 2014). In addition, to increase farmers' confidence in their ability to decrease pesticide use, while maintaining a healthy crop, it should be made more visible to farmers what alternatives to pesticides exist. This stresses the need to inform farmers about alternative, chemical and non-chemical, methods for pest control.

Our third finding shows that the impact of pesticides on the environment seems to play a role in the intentions of our respondents. This suggests that farmers who believe that reducing their pesticide use will benefit nature and environment (i.e., decrease environmental impacts), have a stronger intention to decrease their pesticide use. This is in line with findings of Chèze et al. (2020), who found that farmers' willingness to adopt pesticide reducing practices was motivated by environmental and health gains. Furthermore, Stallman and James (2015) report that farmers who are highly concerned about the negative environmental effects of pesticides are more willing to cooperate to reduce pesticide inputs than farmers being less concerned. In addition, Ahnström et al. (2013) show that farmers' interest in nature was positively associated with higher biodiversity index levels in agricultural landscapes, and explain this as a subconscious factor influencing farm management and management intensity. Thus, here the intrinsic motivation of farmers comes into play. Recent research in the Netherlands confirms the finding that the environmental effects of pesticides weigh heavily in respondents' intention to decrease usage, and suggests to change environmental subsidy schemes from effort-based to result-based (Westerink et al., 2019), feeding into a farmers' feeling of autonomy and reinforcing intrinsic motivations (Reddy et al., 2017). In addition, extension services could focus more on further informing farmers about the impact of pesticides on the environment, and the use of more environmentally friendly products (Skevas and Oude Lansink, 2014).

Finally, we discuss the role of risk attitude on farmers' intentions to decrease pesticide use. We expected that risk avoiding behaviour, such as prophylactic use of pesticides (Chantre and Cardona, 2014), would influence farmer's decision making. In our study, farmers ranked reduced pesticide use as being 'risky', but the relative importance of risk attitude on intentions to decrease pesticide use was offset by the other social-psychological constructs in the model. These findings contrast with previous studies that reported that the risk of large production losses was the main obstacle for farmers to reduce pesticide use (Chèze et al., 2020; Pedersen et al., 2012). Nevertheless, other studies also reported that farmers that were more aware of environmental risks of pesticide use had stronger environmental considerations towards decision-making on pesticide use (Chèze et al., 2020; Pedersen et al., 2012). Yet, our study also indicated that farmers' willingness to reduce pesticide use is, in part, influenced by the belief that reduced pesticide use could reduce crop yield or quality. We cannot rule out the possibility that farmers provided socially desirable answers, but it is equally possible that farmers feel that their 'licence to produce' is at stake and are prepared to change their practices to safeguard their livelihoods in the future. This highlights the need to support farmers with developing low or no pesticide use practices that do not substantially compromise crop performance or profitability (Chèze et al., 2020; Lechenet et al., 2017).

In summary, to trigger intentions to reduce pesticide use, social interactions between farmers should be emphasized, and discussions with peers facilitated, including those that may have opposing views or other management practices, e.g. organic farmers. Furthermore, farmers' sense of control and perceived ability should be strengthened. This can be done through communication and knowledge transfer from a credible and trusted communicator, with a specific focus on alternative pest control options and implications for crop yield and farm income. Moreover, farmers' skills to apply alternative pest control methods (e.g. IPM) should be supported. This could be fostered by, for instance, showcasing successful trials of production with low or no pesticide use at agricultural research stations, experimental farms, or frontrunner farms, and establishing farmer study groups.

5.1. Limitations of the Study and Future Research

In the Netherlands the highest pesticide inputs are reported for flower bulb and vegetable production, which are sectors that are associated with strict quality requirements (Sporenberg et al., 2019). In our study 66% of the 681 respondents were arable farmers, 10% were flower bulb growers, 7% vegetable growers and 18% were fruit growers. While the overall sample size of our study is adequate and is similar or higher than in other studies in this research domain (Breukers et al., 2012; Hijbeek et al., 2018; Läpple and Kelley, 2013), the arable and vegetable growers in our sample were slightly underrepresented, and the fruit and flower bulb growers slightly overrepresented as compared to the Dutch farmer population (Table 1). Nevertheless, multigroup analysis did not show significant differences between farmer groups, implying that our results are representative for the whole farmer population of the Netherlands. Even so, we cannot rule out that our survey did not capture the full heterogeneity in the behaviour and intentions of the Dutch farmer population in regard to reducing pesticide use. For example, there was relatively large variation in farm size in our sample because fruit and vegetable farms are typically smaller than arable farms. Farm size may influence farmer's perceptions and potential pesticide use decision making as larger farms are more efficient in the use of inputs, possibly because they invest more in improving the technology of their inputs (Skevas and Oude Lansink, 2014). Other characteristics, such as age, education and previous knowledge (and experiences) on pesticide use may also influence farmer's attitude and behaviour (Burton, 2014; Fishbein and Ajzen, 2011; Yang et al., 2019). In the Netherlands, all farmers that use pesticides have to comply with national regulations and need to obtain a spraying licence (LNV, 2020), and therefore we assumed that all respondents were knowledgeable on impacts of pesticides on the environment, and that variation in knowledge level was limited. Nonetheless, investigating the responses of specific farm types and farmer characteristics could provide further insights about targeted interventions for particular agricultural sectors.

The RAA, also known as the theory of planned behaviour, is a well-known and frequently applied framework to explain and predict farmer behaviour (Ajzen, 2012; Sok et al., 2020). It focuses on the controlled aspects of decision making and on behaviours that are goal-directed and steered by conscious self-regulatory processes. Farmer's decision making on pesticide management takes place in a business context, and these decisions can have consequences for the private farm business as well as the provisioning of public goods. Assuming that farmers act in this environment as a *homo agricola economicus*, fails to account for behavioural factors that drive pesticide use, such as moral considerations, social influences and one's ability to act in order to achieve an desired outcome. These considerations and peer pressures are captured by the RAA. Furthermore, in a review on behavioural factors affecting the adoption of sustainable farming practices, scholars have recommended to employ experimental research approaches for the ex-ante evaluation of policy designs (Colen, 2016; Dessart et al., 2019). While reasoned action theories have occasionally been applied in a more experimental setting (see e.g., Josefsson et al., 2017), the application of so-called hybrid choice models or integrated choice and latent variable models is a promising approach. In such an approach (see e.g. Sok and Fischer, 2019) a survey experiment is designed which combines the survey measurement of social-psychological constructs with a stated preference experiment (e.g. a discrete choice experiment), which can improve the validity of inductive behavioural research on farmer's behaviour.

6. Conclusion

Our study sheds some light on farmers' intentions to reduce pesticide use to decrease environmental impacts. Our results show that farmers' intention to reduce pesticide use is constrained by social norms, as well as farmers' perceived capability. This suggests that farmers keep a close eye on their neighbours' actions, and it appears that farmers are reluctant to engage in the behaviour of which others disapprove. Furthermore, farmers indicate that they have only limited capacity or autonomy to decrease pesticide use. To conclude, farmers need successful examples of how to decrease pesticide use, which can be through peer farmers or through knowledge provisioning on alternative pest control methods. These insights may be useful to direct policy making and may offer scope to influence farmers' intentions towards pesticide use.

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.

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Appendix A. Supplementary data

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