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Behavioural drivers and barriers for adopting microbial applications in arable farms: Evidence from the Netherlands and Germany

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ABSTRACT

Microbial applications contribute to more sustainable agriculture by stimulating plant growth, increasing resistance to pests and diseases and relieving stresses from climate change. To stimulate the adoption of microbial applications, it is important to understand the underlying reasons for farmers' adoption decision. In this article, we investigate the behavioural drivers and barriers associated with the likelihood to adopt microbial applications. We employ the Behaviour Change Wheel and its capability, opportunity, motivation-behaviour (COM-B) model. Data were collected via an online survey among 196 Dutch and German arable farmers. We find that trust in microbial applications is an important driver and that lack of knowledge and professional support are barriers for the adoption of microbial applications. On this basis, we recommend three interventions: i) norm creation and enablement, ii) education and learning, and iii) trust building by providing incentives. The acceptance and success of a behavioural intervention depends on the choice of the interventionist. For instance, the role of governmental institutions in enforcing the adoption of microbial applications is perceived as problematic by farmers. Instead, farmers expect advisers and farmer organisations to become active in knowledge transmission and field studies.

1. Introduction

Farmers and consecutive supply chain actors are faced with the challenge to feed a growing world population with limited resources. This requires a sustainable increase in production whilst decreasing input use. The European Commission (EC) seeks to increase farming sustainability with their Green Deal and Farm-to-Fork Strategy. The EC's main objective is to reduce chemical and hazardous pesticide use by 50 % and fertiliser use by at least 20 % by 2030 (EC, 2020). In this light, microbial applications in arable farming are important. Microbial applications can decrease the need for plant protection products and fertilisers (Gong et al., 2020; Pertot et al., 2017). Despite recent promising results in the lab and in isolated field trials on the effectiveness of microbial applications, arable farmers are hesitant to adopt these products (Russo et al., 2012).

Microbial applications combine different microorganisms such as bacteria, algae, fungi and viruses (Tshikantwa et al., 2018) with complementing traits (Compant et al., 2019). Certain microorganisms living in the root-soil interface improve productivity and quality of crops, suppress plant diseases and control pathogens (Gouda et al., 2018). Microorganisms stimulate the plant's defence mechanisms (Singh and Trivedi, 2017). They promote plant growth by stimulating biological nitrogen fixation and nutrient uptake (Wezel et al., 2014), dissolving phosphate and relieving abiotic stresses (de Souza et al., 2015).

Microbial applications can supplement or substitute plant protection products and fertilisers (Elnahal et al., 2022). In the EU, they are currently categorised as plant protection products or biocides (Sundh and Eilenberg, 2021), even though they function as biocontrol agents, biostimulants and/or biofertilizers (Marrone, 2019). As such, the definition of microbial applications is not clear-cut. Various studies addressed the discrepancies in the registration and regulation of microbial applications in the EU (Frederiks and Wesseler, 2019; Köhl et al., 2019). In this study we refer to microbial applications as biopesticides and biofertilizers that are sold as granular or in powder form. Both can be put directly in the soil together with the seeds, dissolved in water to use in irrigation, or suspended in liquid for seed coating.

The low adoption rate of microbial applications calls for an investigation of the underlying reasons to use such innovations in arable farming. Recent reviews reveal the determining role of *behavioural* factors in the adoption of sustainable practices and agricultural innovations

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(Streletskaya et al., 2020; Dessart et al., 2019). Therefore, this study aims to answer the following research question: "What are farmers' behavioural drivers and barriers to adopt microbial applications in arable agriculture?" We identify the behavioural factors with a semi-quantitative online survey among Dutch and German arable farmers. Based on the identified drivers for and barriers to adoption, we recommend tailored interventions to support the uptake of microbial applications on arable farms. We do so by employing Michie et al. (2014)'s Behaviour Change Wheel (BCW) as an overarching framework. The BCW is a suitable framework to analyse and change behaviour. The BCW is centred around the capability, opportunity and motivation-behaviour (COM-B) model, which identifies sources of a certain behaviour (Gainforth et al., 2016). Based on this "behavioural diagnosis", relevant types of intervention can be identified (West et al., 2020).

The BCW has thus far mostly been applied to the health and medical context. Examples include prevention behaviour (Gardner et al., 2016; Gould et al., 2017), hygiene (Lydon et al., 2019), medical aid (Barker et al., 2018), physical activity (Webb et al., 2016), and reduction of transmission of the coronavirus disease (COVID-19) (West et al., 2020). A few other applications also focus on the environmental context. Examples include recycling behaviour (Gainforth et al., 2016), a change to energy-related behaviour (Axon et al., 2018) and sustainable food consumption (Hedin et al., 2019). The BCW has rarely been applied in the agricultural context. To the best of our knowledge, there is only one such study on interventions for increasing the frequency of irrigation water sampling and water testing to reduce possible microbiological contamination (Van Asseldonk et al., 2018). The successful introduction of the BCW in these studies suggests it could be useful to study how to stimulate microbial applications in agriculture as well. Furthermore, the BCW has not previously been used to design an online survey. The current article addresses this research gap.

2. Theoretical framework and hypotheses

2.1. The BCW and COM-B model

The BCW is used to design behavioural change interventions. A behavioural change intervention is a set of activities intended to change behaviour. The behaviour that we intend to change is referred to as the "target behaviour". The BCW assumes that behaviour can be altered through changes of intentions, which depend on attitude and perceptions, and the internal and external environment (Michie et al., 2014). The BCW originated in the health and medical sector. Michie et al. (2009) observed that studies in health and medicine successfully identify patterns that cause unhealthy behaviours. Yet, when it came to designing interventions, little of that knowledge was used. As a result, intervention campaigns did not change the underlying causes of unhealthy behaviours and were often ineffective. Further, effective interventions oftentimes could not be replicated, because they were not supported by theory nor a shared terminology (Michie et al., 2009). Therefore, it was difficult to decipher what makes one intervention effective and another one not (Axon et al., 2018). Michie et al. (2005) identified the need to create a theoretical framework that analyses both the causes of behaviour and designs interventions targeted at these specific causes.

Similarly, in the agricultural sector, behavioural causes for low adoption rates of technologies or agri-environmental measures have been investigated and effective interventions were sought based on these findings (Streletskaya et al., 2020). Studies on behavioural causes for low adoption rates of technologies or agri-environmental measures often apply Ajzen (1985)'s "Theory of Planned Behaviour" (TPB) (van Dijk et al., 2016). However, TPB is developed specifically for the analysis of behaviour and does not provide a direct link to interventions.

In contrast, the BCW links models of behaviour with interventions (Michie et al., 2014). The wheel has three layers (see Appendix A for a visualisation of the wheel). The core of the wheel is the capability, opportunity and motivation of the target behaviour, the COM-B model. The COM-B model is used to analyse behavioural causes, for example the reasons for resistance to adopt technologies (Barker et al., 2016). The three elements of the COM-B model are defined as follows (Michie et al., 2011):

- **Capability** represents the **psychological** and **physical** attributes of an individual that enable or facilitate the behaviour. The model distinguishes between knowledge and skills as two separate types of capabilities.
- **Opportunity** describes the environmental factors external to the individual, which enable, facilitate or prevent the behaviour. Environmental factors can be **physical**, such as the lack of tools, or **social**, such as the support by peers. Opportunity and Capability synergistically enable or prevent the behaviour.
- **Motivation** represents the brain processes that energise, demotivate or direct behaviour. Motivation can be **automatic** or **reflective**. Automatic motivations are habitual processes and emotions, while reflective motivations are conscious, analytical decisions.

Fig. 1 illustrates the interdependence of the elements and their influence on the target behaviour. Following Michie et al. (2011), we assume that capability and opportunity influence motivation. All three elements are associated with the target behaviour (Lydon et al., 2019). Each element of the COM-B model is directly linked to interventions and policy recommendations. These are placed in the middle and outer layer of the wheel. The link between the COM-B elements and interventions, enables the translation of research on behavioural causes into practice.

2.2. Hypotheses

In this article, the COM-B model is used to assess the drivers and barriers to adopt microbial applications. The target behaviour is the uptake of microbial applications on the arable farm. The aim is for microbial applications to (partially) substitute chemical plant protection products and fertilisers. We conceptualise the COM-B elements as behavioural reasons to (not) use microbial applications instead of or in addition to conventional production inputs. We interpret each element as a concrete barrier or driver. The elements are defined as follows: **Psychological capability** represents the farmers' knowledge on microbial applications. High scores in psychological capability mean that

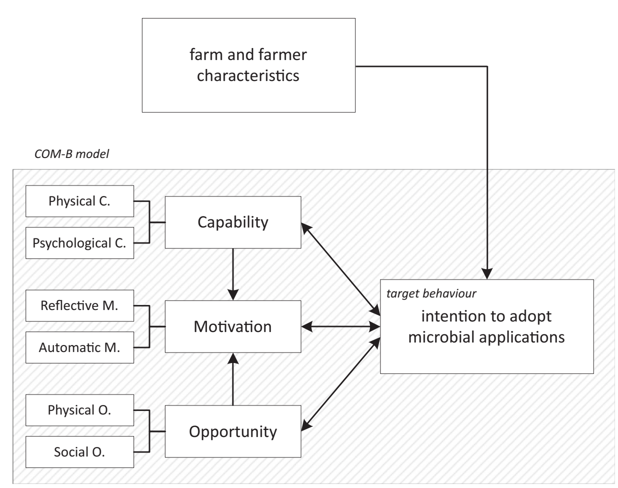

Fig. 1. An overview of the relationships between the concepts and the hypotheses to be tested. We extended the base figure of the COM-B model in Michie et al. (2011, p. 4, Fig. 1) by adding the COM-B sub-elements. We also adjusted the figure to our specific context.

farmers want to understand the effects of microbial applications on crops and the environment. **Physical capability** represents the farmers' tools and machinery needed for the application. Examples include spraying devices such as wing sprayers or machineries for seed coating. Overall, capability-related barriers are lack of knowledge, training and machinery. **Automatic motivations** are subconscious beliefs and habitual processes such as trust in microbial applications. **Reflective motivation** represents a conscious judgement on the positive effects of microbial applications. While capabilities and motivations are always farmer-related, opportunities are environmental factors. **Physical opportunities** are places to purchase microbial applications and to get technical support from advisers, farmer organisations or the government. **Social opportunities** are created when peers or family and friends encourage the use of microbial applications.

We investigate the extent to which each COM-B element is present and related to the adoption of microbial applications. Previous research on the adoption of microbial applications suggests that knowledge, which is reflected in the capability element, lowers the barriers of adoption. Similarly, compatible farm equipment (opportunity) and norm formation (automatic motivation) are drivers for adoption (Parnell et al., 2016; Backer et al., 2018; van Lenteren et al., 2018). We control for farmer characteristics. The only farm characteristic considered is farm type, so whether the farm is an organic or conventional farm. Accordingly, the following pre-registered hypotheses are tested[1]:

1. Farm and farmer characteristics, particularly the year of birth and education,[2] are positively associated with the farmer's likelihood to adopt microbial applications.
2. Capability, Opportunity and Motivation-Behaviour (COM-B) elements are positively associated with the farmers' likelihood to adopt microbial applications.[3]

Fig. 1 visualises the hypotheses and the interrelation of the elements. The interrelation of the COM-B elements is also tested.

3. Data and methods

3.1. Data collection and variables

Based on the BCW and the elements described above, we developed a survey. We collected the data via the online survey software Qualtrics from Dutch and German arable farmers in June–July 2020. The survey conditions were approved in advance by the Social Science Ethical Committee of the authors' institution. The survey was designed in English, translated into Dutch and German and back-translated for quality assurance. Native speakers tested the survey in a pilot phase in every language.

To distribute the link and to collect the data, we followed country-specific strategies. In Germany, we contacted about thirty regional farmer organisations across the country to ask for sharing the link to the survey with a short explanation in their next newsletter. The trade magazine *agrarzeitung* published a short note with the link on their website, in their newsletter and their print magazine. Further, the supra-regional organisations *Deutsche Landwirtschaft Gesellschaft (DLG)* and *Demeter* shared information and the link via e-mail. In the Netherlands, an agency specialised on conducting research among farmers randomly selected 3000 arable farmers from its database. The farmers were contacted individually via e-mail, describing and inviting them to participate in the research. A reminder e-mail was sent a week later. The sampling design described above warrants representativeness in terms of spatial distribution, management type (conventional vs. organic) and farm size. In the Netherlands, we do not have any insights into the composition of the agency's database, but were assured that the sample resembles the population.

The survey consisted of three parts. First, farmers answered questions on their demographics and characteristics of their farm. Part two concerned general attitudes towards the environment and technologies. In part three, we considered microbial applications.

We elicited initial farmers opinions on and knowledge of microbial applications, followed by an informational video. We included the video in the survey to make sure that all participants had a shared knowledge of microbial applications. The video explains the benefits of microbial applications, how they are applied and stored. The video was developed using input from experts, both in microbiology and in agronomy.[4] After the video, we asked farmers about their general perceptions of microbial applications. We asked whether they already use microbial applications (binary: "yes", "no") or how likely they are to do so. The likelihood is measured by a five-point Likert scale where low values stand for "unlikely", high values for "likely" and three is a neutral response.

Finally, we presented the farmers with 15 statements related to the COM-B elements. For capability-and opportunity-related statements we ask *"When it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to…"*. Automatic motivation-related statements start with *"I trust…"*. Reflective motivation-related statements state *"I am confident that microbial applications…"*. There are at least three statements for each COM-B element. Participants indicated on a five-point Likert-scale to what extent they agree or disagree with the statements. A score of three is considered a neutral response, higher values reflect agreement, lower values disagreement. An overview of the statements and related COM-B elements is provided in Table 1.

We also investigated what farmers expect from other actors in the food system. We wanted to know what kind of support is needed to adopt microbial applications. In the survey we asked, "*what should the following stakeholder do to support your adoption?*". Farmers provided open answers on advisers, (farmer) organisations, (local) governments and politics. The answers were translated and coded.

After closing the survey, the raw data (N = 415) were cleaned and analysed using R version 3.6.1.[5] Unnecessary (meta) variables were removed and incomplete answers were excluded. The final sample (N = 196) contains only complete responses of Dutch and German farmers that consented to the terms and conditions of the study. Sixteen respondents did not identify themselves as farmers, managers or principal decision makers of an arable farm, and their answers were therefore omitted from the sample.

3.2. Data analysis

3.2.1. Confirmatory Factor Analysis (CFA)

COM-B elements are latent constructs that cannot be measured directly. Instead, we measure COM-B statement variables. Using the CFA, we created COM-B constructs that are linear combinations of the

[1] The anonymous link to the project is https://osf.io/ey5sd/?view_only=4c06be3445594768ac20dcbbda6499f0; link to preregistration: https://doi.org/10.17605/OSF.IO/3WB24

[2] Farm size was also pre-registered, but not included in the survey

[3] Please note that in the original pre-registration, we used the phrase 'willingness to adopt' as the term is widely used in the agricultural adoption literature (for instance Möhring and Finger (2022); Teff-Seker et al. (2022); Zeweld et al. (2017). However, in the survey, we asked the farmers to evaluate the 'likelihood' of adoption. To be consistent, we stick to the term 'likelihood'.

[4] The anonymised video file is provided in the following OSF project: https://osf.io/ey5sd/?view_only=4c06be3445594768ac20dcbbda6499f0. The participants had to answer three comprehension questions. The questions were based on the video and tested whether they watched it attentively. There is no evidence of structural misunderstanding or unperceptive watching behaviour.

[5] The R code will be made available in the online supplementary material and in the OSF project.

Table 1
Original COM-B elements, sub-elements and variables with question text. Model tested in CFA.

COM-B elements		Variable	Statement
Main $\overline{E}_{je}$	Sub $\overline{S}_{je}$	x_i	*When it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to...*
Capability	Psychological	Understand	understand the effect of microbial applications.
		Effect on plants	know how microbial applications affect crops.
		Effect on soil	know how microbial applications affect the soil.
	Physical	Training needed	attend a training to be able to use microbial applications.
		Machinery needed	acquire necessary machinery to deliver microbial applications.
Opportunity	Physical	Purchase	know where to purchase microbial applications.
		Support	get support from advisers/farmer organisations/the government to adopt microbial applications.
	Social	Approval	get approval from my family/friends and other farmers in my network to adopt microbial applications.
Motivation	Automatic		*I trust...*
		Trust Efficacy	the efficacy of microbial applications.
		Trust Safety	the safety of microbial applications.
	Reflective		*I am confident that microbial applications...*
		Soil health	improve soil health.
		Resistance	increase crop resistance to extreme weather events (e.g. droughts).
		Plant health	improve plant health.
		Farmer health	improve my health.
		Consumer health	improve consumers' health.

Notes. All COM-B variables are measured on a five-point Likert scale, where high values denote agreement, low values disagreement and 3 a neutral response.

statement variables. The CFA helps us to understand whether the different statements used to elicit one COM-B element indeed belong to the same element. An estimation model determines the appropriate statements (Micheels and Nolan, 2016). With a CFA one generally evaluates hypothesised structures of latent constructs. In our case, the hypothesised structure is the allotment of the COM-B statement variables to specific COM-B elements.

Using the CFA, we constructed latent variables. To get from statements via latent variables to individual observations, we used the estimates provided by the CFA: We calculated the individual score of each COM-B element for each participant. With the parameter estimates β_i provided by the CFA, the sub-score S_{je} of each participant j per sub-element e is calculated as follows:

$$\overline{\mathbf{S}}_{je} = \sum_{i=1}^{I} \widehat{\beta}_i x_i, \tag{1}$$

Here, x_i is the observed Likert-scale value for each variable i. The scores of the main COM-B elements E_{je} consist of the sum of its sub-elements. For example, physical and social opportunity are the sub-elements of the main element opportunity.

$$\overline{E}_{je} = \overline{\mathbf{S}}_{je_1} + \overline{\mathbf{S}}_{je_2} \tag{2}$$

This holds for all three COM-B elements and their sub-scales. To test the interrelationship of the COM-B main elements (as depicted in the inner box of Fig. 1), we conducted an ordinary least square (OLS) regression analysis with the latent motivation element as the dependent variable and opportunity and capability as independent variables. We call this the COM-B OLS regression analysis.

On the statement variables we conducted a preliminary correlation analysis, Kurtosis test and skewness test to identify extreme outliers. Observations with Kurtosis values outside the range of −1 and 1 were considered extreme outliers. Cronbach's alpha of the latent COM-B constructs was compared to its threshold level of 0.7 (Cortina, 1993). The model fit was judged based on a set of three fit indices: the model Chi-square test for over-identified models, incremental indices, such as the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), and the Root Means Square Error of Approximation (RMSEA) as an absolute fit index.

3.2.2. Regression analysis

We used regression analyses to evaluate the factors associated with the uptake of microbial applications. The relationship between COM-B elements and microbial application use offers insights on the drivers and barriers of adoption. We distinguish between a usage and a likelihood to adopt model. Usage of and likelihood to adopt microbial applications are dependent variables. The usage model is a binary probit model, the likelihood to adopt model is an ordered probit model. COM-B elements and farm characteristics are independent variables. This leaves us with in total six models, belonging to two families, describing usage and likelihood. See Table 2 for an overview. The independent variables are i) farm and farmer characteristics (hypothesis 1), ii) the main COM-B elements (hypothesis 2) and iii) control and COM-B variables in one overarching model.

3.3. Descriptive statistics

The final data set contains 133 Dutch (68 %) and 63 German (32 %) farmers. The response rate with respect to the completed surveys is 4.43 % in the Netherlands. The response rate is somewhat lower than the response rate of comparable studies, and similar when all initial responses are included. We cannot compute the German response rate due to the voluntary response sampling method. Being predominantly male (93 %) and with an average age of 52 ± 12 years, our sample provides a reasonable reflection of the farming population with regards to gender and age. According to Eurostat data (Eurostat, 2020), 57 % of EU farmers are between 40 and 65 years old. In our sample, almost half of the farmers hold a university degree (46 %) and the majority (70 %) received a full agricultural education. According to Eurostat (2021), in total 9.5 % of the Dutch and 17 % of the German farmers received a full agricultural education in 2016. In comparison to the figures in Table 4, our sample is far better educated.

Seven percent of the farms in the sample are certified organic. In the EU, in total 7.5 % of the farmland is organic (Eurostat, 2019). However, in 2018, just five member states accounted for more than half of all organically farmed land, among which Germany (9.1 %). According to the most recent (2016) Eurostat data, 3 % and 10 % of farms in the Netherlands and Germany, respectively, were organic with an increasing trend over the last years. In our sample, 5 % of the Dutch farms and 11 % of the German farms are organic. Thus, our sample resembles the population with regards to the proportion of organic farms. A summary and overview of the descriptive statistics is provided in Tables 3 and 4. Additional descriptive statistics on farmer attitudes on innovations, the environment, climate change and soil quality and the use of microbial applications, are provided in Appendix B and Appendix C.

The representativeness of the sample is limited. First, in Germany, the only sampling option was a voluntary response sample. Thereby, sampling biases might have been introduced. For instance, farmers that are already interested in microbial applications might have been more

Table 2
Overview of regression models and their equations.

	Usage (y/n)	Likelihood (1–5)
i) Demographics	$Pr\left(a_j = 1 \middle| D_{jn}\right) = \phi\left(\beta_0 + \sum_{n=1}^{N} \beta_n D_{jn} + \epsilon_j\right)$ $Pr\left(a_j = 0 \middle| D_{jn}\right) = 1 - \phi\left(\beta_0 + \sum_{n=1}^{N} \beta_n D_{jn} + \epsilon_j\right)$	$Pr\left[y \leq i \middle| D_{jn}\right] = F\left(\kappa_i - \sum_{N}^{n=1} \beta_n D_{jn} - \epsilon_j\right)$ $i = 1, \ldots, I$
ii) Main COM-B	$Pr\left(a_j = 1 \middle| E_{je}\right) = \phi\left(\beta_0 + \sum_{e=1}^{E} \beta_e E_{je} + \epsilon_j\right)$ $Pr\left(a_j = 0 \middle| E_{je}\right) = 1 - \phi\left(\beta_0 + \sum_{e=1}^{E} \beta_e E_{je} + \epsilon_j\right)$	$Pr\left[y \leq i \middle| D_{jn}\right] = F\left(\kappa_i - \sum_{e=1}^{E} \beta E_{je} - \epsilon_j\right)$ $i = 1, \ldots, I$
iii) Overall model	$Pr\left(a_j = 1 \middle| D_{jn} E_{je}\right) = \phi\left(\beta_0 + \sum_{n=1}^{N} \beta_n D_{jn} + \sum_{e=1}^{E} \beta_e E_{je} + \epsilon_j\right)$ $Pr\left(a_j = 0 \middle| D_{jn} E_{je}\right) = 1 - \phi\left(\beta_0 + \sum_{n=1}^{N} \beta_n D_{jn} - \sum_{e=1}^{E} \beta_e E_{je} \epsilon_j\right)$	$Pr\left[y \leq i \middle| D_{jn}\right] = F\left(\kappa_i - \sum_{n=1}^{N} \beta_n D_{jn} - \sum_{e=1}^{E} \beta_e E_{je} - \epsilon_j\right)$ $i = 1, \ldots, I$

Notes. a is the usage Boolean variable, 0 denotes "not using microbial applications" and 1 denotes "using microbial applications". A binary probit model is estimated. Φ denotes a cumulative probability function.
y is the observed likelihood to adopt on an ordered categorical scale from one to five $y \in 1, \ldots, I$ where I denotes the different likelihood levels. Higher values denote a high likelihood to use microbial applications, lower values denote a small likelihood. κ_i are the unknown threshold parameters that divide the slope into I categories. F is a cumulative standard normal distribution. An ordered probit model is estimated.
D_{jn} is a matrix of farm j specific demographic variables n and β_n the associated estimated coefficients. β_0 is the intercept. E_{je} is the farm j specific score of the e^{th} element of the main COM-B elements and β_e the associated coefficients. ϵ_j is the unobserved error term.

Table 3
Descriptive statistics .

	Sample			The Netherlands			Germany		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Age	190	51.86	11.52	132	53.57	10.75	58	47.98	12.35
Household size	187	3.51	1.42	128	3.29	1.39	59	4.00	1.39
Expenditure (in €)	154	12,999.79	23,940.63	102	13,173.82	25,312.40	52	12,658.40	21,222.75
% for environment	175	32.60	22.69	118	29.67	23.65	57	38.67	19.38
% for profit	171	40.06	23.90	116	35.69	24.39	55	49.27	20.11
% to improve health	150	28.51	23.25	101	28.03	23.96	49	29.49	21.93

keen to participate in the survey. Second, the final response rate of completed surveys in the Netherlands is significantly lower than in comparable studies (Hannus et al., 2020; Munz et al., 2020; Reijneveld et al., 2019). Reasons for the low response rate may be the timing of the data collection in summer, the length of the survey, and the absence of financial compensation, all of which have been found to lower their willingness to participate (Pennings et al., 2002). In addition, several replies from farmers indicated a fatigue in participation to (online) studies. Third, since the survey was held on-line, farmers with limited digital literacy skills are automatically excluded, leading to a selection bias. Last, the descriptive statistics show that the sample is better educated than the average farmer population. All in all, these factors decrease the generalisability of our results. Our survey represents the higher educated and motivated farmers.

Table 4
Descriptive statistics .

Statistic	Sample		The Netherlands		Germany	
	N	%	N	%	N	%
Country	196		133	68 %	63	37 %
Male	183	93 %	127	95 %	56	98 %
Education						
Secondary school	19	7 %	6	5 %	13	21 %
High school	86	43 %	77	58 %	9	14 %
Higher education	91	46 %	50	38 %	41	65 %
Agricultural education						
Basic	19	10 %	14	11 %	5	8 %
Practical	37	19 %	27	20 %	10	16 %
Full	138	70 %	90	68 %	48	76 %
Member organisation	149	76 %	101	76 %	48	76 %
Organic farming	13	7 %	6	5 %	7	11 %
Full-time farmer	63	69 %	102	76 %	31	50 %
Percentage of income from farming						
If not full-time farmer						
0–20 %	20	10 %	10	8 %	10	16 %
21–40 %	12	6 %	5	4 %	7	11 %
41–60 %	16	8 %	11	8 %	5	8 %
61–80 %	7	4 %	1	1 %	6	10 %
81–100 %	8	4 %	4	3 %	4	6 %

4. Results

4.1. Estimation of COM-B elements using CFA

The preliminary analysis does not call for exclusion of any variables from the subsequent analysis. Based on the Kurtosis test, COM-B statement variables did not have significant outliers. The majority of observations were within the acceptable range between −1 and 1. Only a few variables were just outside the range. The skewness test provided a similar picture. Only three of the sixteen COM-B variables have a skewness value of at least one. Most variables were slightly skewed to the right (rather agree than disagree). The Kurtosis and skewness values are provided in Appendix D1 for completeness. The correlation analysis reveals that the majority of the statement variables have a significant positive correlation with each other (see Appendix E1).

The p-value of the model's Chi-square is smaller than 0.001, which usually indicates a poor model fit. We ran an exploratory factor analysis (EFA) to make sure that there was no better fitting model for our data. The resulting EFA model Chi-square test is similarly significant. This study intends to test whether the COM-B model is a suitable model in the context of agricultural innovation adoption. Therefore, we stick with the original CFA model. In addition, standardised loadings and other indicators suggest that the model describes the data well (CFI = 0.94, TFI = 0.92, RMSEA = 0.07). Overall, we conclude that there is no better alternative to the proposed COM-B model, but we acknowledge the limitations of the model. The limitations are discussed in Section 5.3.

The Cronbach's alpha values for each of the three COM-B elements and their sub-elements show that the opportunity element does not meet the threshold for internal consistency. This is due to the small number of variables measured to compute the latent factor. We refer to Table 5 for estimates, fit indices and Cronbach's alpha values.

The factor loadings are coefficients between the observed COM-B statement variables and the latent COM-B constructs. Based on the factor loadings, we interpret the COM-B elements as follows. The coefficient of physical capability is higher than psychological capability (Table 5). Thus, in this context, **capability** refers mainly to physical attributes, such as tools and machinery, enabling or facilitating the uptake of microbial applications. **Opportunities** are to a large extent understood as physical opportunities, namely support provided by the professional network and knowledge of purchase points, and less so as approval from private reference points. **Motivation** is equally described by automatic and reflective motivation. Motivation entails trust in the efficacy and safety. Motivation also includes reflections on the benefits of microbial applications with respect to resistance, soil and plant health.

The COM-B OLS regression results that are presented in the following, deliver seemingly contradictory results to what we see in Fig. 2. According to the COM-B OLS regression results, capability has a significantly positive effect on motivation ($b = 6.51$, $t(193) = 17.13$, $p < 0.001$) and opportunity has a significantly negative effect on motivation ($b = -3.66$, $t(193) = -14.33$, $p < 0.001$). The adjusted R^2 of the simple regression model is 0.77. While opportunity is negatively associated with motivation in the COM-B OLS regression model, the correlogram in Fig. 2 visualises that the variables are positively correlated. The reason for this contradiction is the relationship between opportunity and capability. Opportunity and capability are almost perfectly collinear ($r(194) = 0.99$, $p < 0.001$). The Pearson correlation coefficients of capability and opportunity are $r(194) = 0.73$ ($p < 0.001$) and $r(194) = 0.65$ ($p < 0.001$), respectively. This means that the variation of the motivation variable is captured almost entirely by the capability variable and the results are not contradictory. Nonetheless, the findings reveal other issues with the model, which are discussed in Section 5.3. All sub-elements are significantly and highly correlated with the respective main COM-B elements (all with $p < 0.001$). A complete overview of the correlations between all COM-B elements and sub-elements is given in Appendix E.

Table 5
Results of the Confirmatory Factor Analysis, including Cronbach's α.

Factor loadings					
Ordinary COM-B model		Standardised[a] COM-B model			Cronbach's
	Estimate	Estimate	SE	p	α
Psychological capability (*C.psy*)					0.90
Understand	1.00	0.68	0.06	0.00	
Effect on plants	1.15	0.81	0.05	0.00	
Effect on soil	1.16	0.79	0.05	0.00	
Physical capability (*C.phy*)					0.75
Training need	1.00	0.28	0.126	0.02	
Machinery need	1.03	0.25	0.11	0.02	
Funds need	1.16	0.27	0.12	0.02	
Automatic motivation (*M.aut*)					0.72
Efficacy	1.00	0.28	0.16	0.09	
Safety	0.91	0.23	0.13	0.082	
Reflective motivation (*M.ref*)					0.77
Soil health	1.00	0.46	0.07	0.00	
Plant health	1.09	0.51	0.08	0.00	
Farmer health	0.49	0.20	0.10	0.00	
Consumer health	0.53	0.18	0.05	0.00	
Resistance	1.04	0.48	0.08	0.00	
Physical opportunity (*O.phy*)					0.56
Support	1.00	0.26	0.12	0.03	
Purchase	1.07	0.29	0.13	0.03	
Social opportunity (*O.soc*)					/
Approval	1.00	0.84	0.05	0.00	
Capability (*C*)					0.81
C.psy	1.00	0.57	0.10	0.00	
C.phy	1.78	2.41	1.21	0.05	
Motivation (*M*)					0.82
M.aut	1.00	2.78	1.79	0.12	
M.ref	0.89	1.44	0.32	0.00	
Opportunity (*O*)					0.59
O.phy	1.00	2.04	1.06	0.05	
O.soc	1.25	0.63	0.11	0.00	

Fit indices				
	Ordinary COM-B model		Standardised COM-B model	
χ^2(df)	184.27(96)	$p = 0.00$	184.27(96)	$p = 0.00$
CFI	0.94		0.94	
TLI	0.92		0.92	
RMSEA	0.07		0.07	

Notes. lavaan 0.6–6 ended normally after 65 iterations.
[a] Standardised such that latent and observed variables have a variance of one.

4.2. Regression analysis: drivers and barriers of adoption

In total, we estimated six regression models belonging to two different families. We distinguish between a binary probit model, where adoption is the dependent variable, and an ordered probit regression model, where likelihood to adopt is the dependent variable. We run three models in each family: i) with the pure demographics, only, ii) the main COM-B elements, and iii) the overall model, in which the first two are combined. In the binary probit model, motivation is significantly and positively associated with the use of microbial applications ($\beta = 1.40$, $p = 0.00$). Capability and opportunity are significantly associated with the likelihood to adopt (C: $\beta = 10.44$, $p = 0.02$; O: $\beta = -5.39$, $p = 0.04$).

The results of the regression analyses on usage and likelihood to adopt microbial applications are presented respectively in Tables 6 and 7. In the usage model with respect to farmer characteristics, we identify a weakly significant negative association of age ($\beta = -0.04$; $p = 0.02$) and a positive association of organic farming ($\beta = 1.08$, $p = 0.09$). Farm management type is not significantly associated with the likelihood to adopt.

To verify any combined effect of farm characteristics and the COM-B model elements, we ran a regression analysis with the COM-B elements and control variables. With regard to usage, when controlling for demographic characteristics, motivation is still highly significant. Additionally, younger farmers are more likely to use microbial applications. In the overarching model, also capability and opportunity become significant on the $\alpha = 0.9$ level. With regards to likelihood, the combined model delivers the same results as in the uncontrolled regression model. None of the farmer characteristics is significantly associated with likelihood to adopt microbial applications. Instead, capability and opportunity jointly affect the likelihood to adopt microbial applications. Capability and Opportunity are significantly associated at the $\alpha = 0.9$ level. Opportunity is negatively associated with the likelihood to adopt microbial applications.

All in all, we reject the first hypothesis that farm and farmer characteristics are positively associated with the likelihood to adopt microbial applications. We only find a weak association between the age of the farmer and usage of microbial applications. We fail to reject the second hypothesis on an association between COM-B model elements and farmer's likelihood to adopt microbial applications.

4.3. Supporting the uptake of microbial applications

Regarding the support desired from others, we find through the qualitative analysis that farmers perceive knowledge transmission and research communication as the two most important tasks. Farmers expect advisers to acquire and disseminate up-to-date knowledge, and provide clear advice. Further, farmers ask for independent, long-term

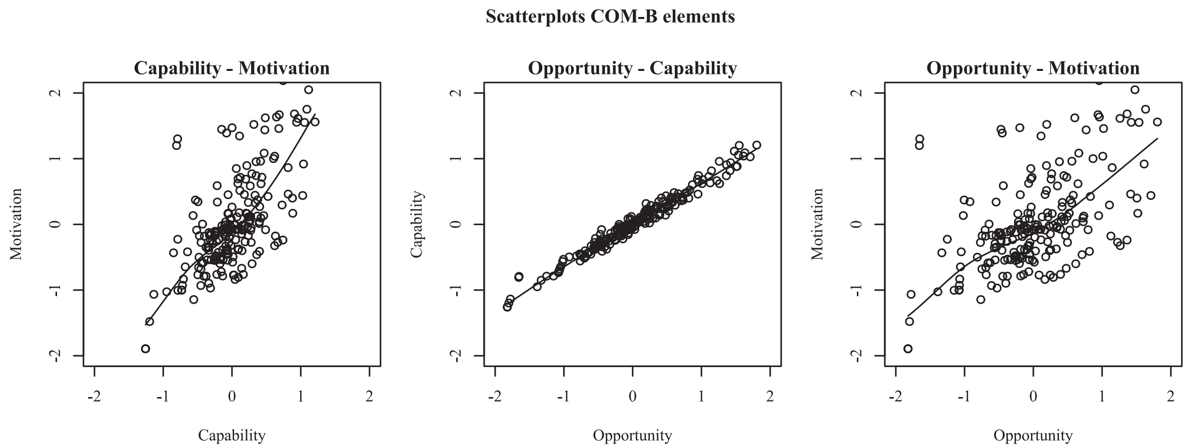

Fig. 2. Scatterplots COM-B element

Table 6
Results of the "usage" binary probit regression analysis with different independent variables; Dependent variable: Usage of microbial applications (1: yes, 0: no).

	Demographics		COM-B		Overall	
	Estimate (SE)	p (z)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Constant	0.52	0.70	−0.75	0.00	0.56	0.71
	(1.39)	(0.38)	(0.16)	(−4.66)	(1.51)	(0.37)
Country: The Netherlands	0.18	0.65			0.12	0.78
	(0.41)	(0.45)			(0.44)	(0.28)
Gender: Male	0.22	0.75			0.27	0.73
	(0.71)	(0.31)			(0.79)	(0.35)
Age	−0.04	0.02			−0.04	0.03
	(0.02)	(−2.37)			(0.02)	(−2.20)
Off-farm job: yes	−0.13	0.75			−0.44	0.31
	(0.39)	(−0.32)			(0.43)	(−1.03)
Education level						
Higher education	0.21	0.74			0.53	0.45
	(0.63)	(0.34)			(0.70)	(0.76)
High school graduate	−0.26	0.69			0.03	0.97
	(0.66)	(−0.40)			(0.73)	(0.04)
Agricultural education level						
Practical ag. experience	−0.32	0.66			−0.59	0.45
	(0.72)	(−0.44)			(0.77)	(−0.76)
Full ag. training	0.13	0.83			0.22	0.73
	(0.60)	(0.21)			(0.64)	(0.34)
Farmer organisation: yes	0.06	0.88			−0.17	0.70
	(0.42)	(0.15)			(0.45)	(−0.39)
Organic: Yes	1.08	0.09			0.86	0.21
	(0.64)	(1.67)			(0.68)	(1.26)
Household	0.06	0.61			0.01	0.92
	(0.12)	(0.52)			(0.13)	(0.10)
Capability			−5.68	0.15	−8.25	0.07
			(3.97)	(−1.43)	(4.56)	(−1.81)
Opportunity			3.40	0.16	4.95	0.07
			(2.41)	(1.41)	(2.76)	(1.80)
Motivation			1.40	0.00	1.70	0.002
			(0.48)	(2.92)	(0.55)	(3.10)
Observations	179		195		195	
Null deviance (df)	229.68 (178)		248.24 (194)		229.68 (178)	
Residual deviance (df)	215 (167)		231.32 (191)		198.03 (164)	
AIC	239		239.32		228.03	

Table 7
Results of the 'likelihood to adopt' ordered probit regression analysis with different independent variables; Dependent variable: likelihood to adopt microbial applications (1: very unlikely, 3: neutral, 5: very likely).

	Demographics		COM-B		Overall	
	Estimate (SE)	p (t)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Constants						
1 | 2	1.68	0.27	−0.66	0.00	0.47	0.78
	(1.54)	(1.09)	(0.20)	(−3.26)	(1.65)	(0.28)
2 | 3	3.38	0.03	1.30	0.00	2.63	0.12
	(1.56)	(2.16)	(0.23)	(5.61)	(1.68)	(1.56)
3 | 4	4.30	0.01	2.46	0.00	3.86	0.02
	(1.58)	(2.72)	(0.33)	(7.51)	(1.70)	(2.27)
4 | 5	5.00	0.001	3.23	0.00	4.78	0.01
	(1.60)	(3.12)	(0.43)	(7.54)	(1.74)	(2.75)
Country: The Netherlands	0.27	0.58			0.04	0.94
	(0.48)	(0.56)			(0.50)	(0.08)
Gender: Male	1.00	0.21			1.29	0.15
	(0.79)	(1.26)			(0.90)	(1.44)
Age	−0.002	0.88			−0.01	0.74
	(0.02)	(−0.15)			(0.02)	(−0.33)
Off-farm job: yes	−0.20	0.64			−0.52	0.27
	(0.43)	(−0.47)			(0.47)	(−1.10)
Education level						
Higher education	−0.54	0.45			−0.33	0.67
	(0.71)	(−0.76)			(0.79)	(−0.42)
High school graduate	−0.37	0.60			−0.20	0.80
	(0.71)	(−0.52)			(0.80)	(−0.26)
Agricultural education level						
Practical ag. experience	1.18	0.11			1.23	0.12
	(0.74)	(1.60)			(0.80)	(1.54)
Full ag. training	1.29	0.06			1.07	0.14
	(0.69)	(1.87)			(0.73)	(1.47)
Farmer organisation: yes	0.45	0.09			0.28	0.59
	(0.46)	(1.70)			(0.50)	(0.54)
Organic: Yes	1.26	0.16			0.57	0.62
	(0.91)	(1.40)			(1.13)	(0.50)
Household	−0.06	0.67			−0.19	0.18
	(0.13)	(−0.43)			(0.14)	(−1.33)
Capability			10.44	0.02	11.37	0.03
			(4.44)	(2.35)	(5.31)	(2.14)
Opportunity			−5.39	0.04	−5.95	0.06
			(2.66)	(−2.02)	(3.16)	(−1.88)
Motivation			0.03	0.95	0.32	0.61
			(0.55)	(0.06)	(0.64)	(0.51)
Observations	117		192		183	
Residual deviance	298.59		295.84		254.62	
AIC	324.59		309.84		290.62	

and large-scale field studies and research. Farmers also see their farmer organisations as important accelerators. They expect them to organise knowledge-sharing events. Governments and policy makers should, according to many farmers, not do anything except for providing funds and stimulating research. Example quotes are provided in Table 8.

5. Discussion

5.1. Drivers and barriers for adopting microbial applications

We estimate two separate models, the binary usage and the ordered likelihood to adopt model, to investigate the behavioural drivers and barriers for adopting microbial applications. The difference between the models is that with the former we investigate farmers that are already using microbials and with the latter we investigate farmers potential likelihood to adopt microbial applications. Thus, the farmers in the two different models have different initial stances towards microbial applications. We find that the drivers and barriers are different in these two models. Our empirical results show that motivation is a behavioural driver in the usage model. In the likelihood to adopt model, opportunity appears to be a behavioural barrier and capability a behavioural driver.

Motivation, which in our context constitutes trust in microbial applications' efficacy and safety, is a crucial driver for microbial application usage. This result from the regression analysis is complemented by the qualitative evaluation of the farmers on what different stakeholders should do to support the uptake: Numerous farmers demand large-scale and long-term field studies to investigate the efficacy of microbial applications. Evidence of a positive effect of microbial application is the basis for trust in the product's efficacy and safety, which is the core of the motivation element. A strong motivation encourages the use of microbial applications.

Opportunity, which constitutes a behavioural barrier to the likelihood to adopt microbial application, is mainly understood in this study as support provided by professional networks and knowledge of purchase points. The results of our regression analysis indicate that when support is needed, the likelihood to adopt microbial applications is negatively affected. The analysis of the qualitative results complements these empirical findings: while the support of knowledgeable advisors

Table 8
Example answers provided by farmers to the question: *What should the following stakeholder do to support your adoption?*

	Advisers	Farmer organisations	Government	Politics
Knowledge	Acquire knowledge; Sharing practical knowledge; spread knowledge	Dissemination of knowledge; Facilitating knowledge transfer between colleagues	0.00 knowledge available at local authorities	
Research	Large-scale in-dependent field study; independent research pilot farms (prove what it adds); disseminating practical research data; To come up with results of independent research from the experimental farm	Farmers' organisations initiate testing and identify the positive effects of the application on trial fields, etc. when they propagate this, the sec-tor will take up the application	Subsidising research and influencing public opinion; stimulating research; re-search awareness local authorities should also know more about what we do	Make money available for tests
Advice		Take note and ad-vise and support whether or not positively		
Information	Information on applications, existing products, crop yields and financial consequences	Disseminate information, promote		
Other				Allowing producers to have a good range available for the practice

and farmer's organisations is desired, governmental and political incentives are perceived questionable by farmers.

Capability, especially in the sense of understanding and knowledge on microbial applications, is a driver to the likelihood to adopt microbial applications. It coincides with "perceived behaviour control" in the "Theory of Planned Behaviour" (Ajzen, 1985) and a recent study on the reduction of pesticide use finds that farmers perceive their control over the amount of pesticide use as limited (Bakker et al., 2021)

5.2. Intervention recommendation

One of the BCW's strengths is its direct link of the COM-B drivers and barriers with intervention functions. As a reminder, the BCW consists of three layers. The intervention functions in the second layer of the wheel are methodically connected to the COM-B model at the core of the wheel (Michie et al., 2011). The BCW shows which COM behavioural deficits can be approach through which intervention functions. In the following, we hypothetically connect our empirical findings on COM-B drivers and barriers to adopt microbial applications to BCW intervention recommendations for farmers.

The first group of interventions is referred to as "build trust, provide incentives". This intervention targets the motivation element of the COM-B model and relates to our qualitative findings. Through large-scale and long-term field studies under realistic conditions, trust can be created. By providing proof that microbial applications work, motivation might be increased so that farmers are more inclined to use microbial applications on their fields.

The second group of interventions is referred to as "norm creation". The BCW suggests that opportunity can be achieved through environmental change, restructuring and an enabling environment (Manda et al., 2020; Michie et al., 2011). A supportive social context encourages the adoption of microbial applications (Michie et al., 2014). Guided by the BCW, we recommend raising awareness among farmers on microbial applications and their benefits. We recommend increasing general knowledge on the role and importance of microbial applications and conveying practical and technical information. For example, it should be clear where to buy microbial applications.

The last group of interventions, "learning and education", targets the capability element. Through learning and education, a sense of control can be generated. Here, we do not refer to general schooling or agricultural education, but to specific trainings and information provision on microbial applications. Specific recommendations for training and education interventions can be drawn from the literature on learning and information transmission. Previous research suggests that a combination of extension services and social learning strongly predicts technology adoption (Genius et al., 2014; Yigezu et al., 2018). Social learning refers to the informal exchange of information among peers. Extension services are most effective if there is already a critical mass of adopters. Further, peers can provide first-hand experience with microbial applications (Ojo et al., 2021). Peer-to-peer exchange facilitates social learning and increases the effectiveness of the extension services (Khataza et al., 2018). This group of interventions targets both farmers and extension services and organisations. Our qualitative results show that extension services, advisers and farmer organisations are crucial actors, while there is scepticism towards policy-makers and the government as a source of information.

5.3. Limitations of the BCW and this study

The BCW with its COM-B model has rarely been applied in the agricultural context nor has it been used to design an online survey. The current article addressed this research gap and in the following we report key limitations of the BCW and its COM-B model alongside limitations of this study.

First, we find that the BCW step-by-step process as detailed in Michie et al. (2014), is too resource-intensive and difficult to execute in practice. We acknowledge that a two-step process, with an exploratory qualitative study followed by a semi-quantitative study, would be the best way to apply the BCW. However, an iterative process cannot be applied in all cases, as for example study participants might not be available anymore (Gould et al., 2017).

Second, we find that the BCW cannot be applied seamlessly in a semi-quantitative study. In semi-quantitative online surveys, the BCW's comprehensiveness becomes a weakness. We saw that our survey instrument was tiring for participants which decreased the number of complete responses and data quality. At the same time, a high number of variables usually ensures that all possible drivers and barriers of the adoption are investigated. At least two (preferably three) statement variables per sub-element are needed to get satisfactory information from latent COM-B constructs. In our application, the opportunity element was under-represented. In addition, the physical opportunity element did not explicitly take subsidies into account. In the context of agricultural policy, this is an important element that is missing (Wilson and Marselle, 2016). In future research, considerable effort should be made to find just the right amount of questions - not too many to bore participants, and not too little to elicit all necessary aspects.

Further, as latent COM-B elements cannot be observed directly, they need to be translated one-by-one into context-specific variables and questions. In this study, the choice and number of statement variables were the root causes of its key limitation. For instance, one of the main COM-B questions, “when it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to...” might not be applicable to all farmers in the sample. It is crucial that the survey questions appeal to a wide range of farmers with different adoption levels and demographic backgrounds. Further, the answer options might not have been intuitive or needed re-interpretation by the farmer. This could have introduced variability to the data that cannot be statistically detected. To avoid this kind of ambiguity, validated COM-B survey instruments would be needed (Willmott et al., 2021). In general, the COM-B model might be more suited for qualitative, observational studies unless there are validated, pre-tested survey instruments which can be used reliably in various different contexts.

Third, our results are ambiguous with regard to the COM-B model. On the one hand, the Chi-square results indicate a poor model fit. On the other hand, other fit indices show that the model describes the data well. According to Xia and Yang (2019), “achieving a set of desired values of RMSEA, CFI, and TLI is one marker showing that the model [is] successful”, but still also other modelling options should be explored (p 421). We used EFA to do so. The resulting EFA model did not provide a better alternative in terms of fit. Instead, the ambiguity of our results might be rooted in the chosen statement variables, which affirms the need for a validated survey instrument.

Fourth, the COM-B OLS regression analysis revealed additional limitations of the model. We saw that the model is over-fitted since the variation of the motivation variable is captured almost entirely by the capability variable. Likely, the model does not capture the latent opportunity variable because of the small number of statement variables. Also, per definition of the model, the behavioural intention variable is a confounding variable (as depicted in Fig. 1) that is not taken into account in our COM-B OLS regression analysis. It might be the case that the behaviour variable explains all or part of the COM elements.

For future research, we want to stress the importance of conciseness, reference to the farming context and clarity of the survey questions. Customisation of survey questions might be as crucial as validation of survey instruments. Despite the limitations of the survey instrument and the previously mentioned limitations of the composition of the sample, our results provide first insights into the behavioural drivers and barriers for the adoption of microbial applications. Our results are not generalisable, but provide a basis for future research, which is discussed in the following concluding section.

6. Conclusion and recommendations

This study investigated the drivers and barriers to adopting microbial applications on Dutch and German arable farms. We hypothesised that i) farm and farmer characteristics and ii) the COM-B elements might come into play when making adoption decisions. The results suggest that none of the farm or farmer characteristics are associated with the likelihood of adoption or usage of microbial applications. We find evidence of a positive correlation between the COM-B elements of the BCW and the farmers' likelihood to adopt microbial applications. The results reveal the behavioural drivers and barriers to adopt microbial applications. We applied two distinct models. In the first model, we investigate usage of microbial applications and find that motivation is an important driver. In the second model, we investigate the likelihood to adopt and find that capability is an important driver and opportunity a barrier.

One of the advantages of the BCW is that COM-B drivers and barriers are directly linked with potential intervention strategies. We linked our empirical findings to BCW-based intervention strategies and recommend three interventions summarised as i) norm creation and enablement, ii) education and learning and iii) building trust by providing incentives. Our qualitative data complement these recommendations: Our results suggest that large-scale and long-term field studies are needed to motivate microbial application adoption. Further, we find that farmers in particular expect advisers to acquire up to date knowledge, to enable dissemination and provide clear advice.

We have four recommendations for further research. First, we recommend using the findings on the barriers and drivers for the adoption of microbial applications of this study to initiate stakeholder discussions. The aim of these stakeholder discussions should be to verify and eventually adjust or complement the identified drivers and barriers. Thereby, the COM-B model can be adapted to the agricultural context. Second, we recommend developing and validating COM-B survey elements that are applicable and adaptable to a range of contexts. Currently, it is resource-intensive to use the COM-B model in semi-quantitative online surveys. Pre-defined COM-B statements and a rapid step-by-step process facilitate the use of the BCW. Third, we recommend investigating whether the suggested intervention strategies increase the adoption of microbial applications. The effectiveness of interventions can be tested in randomised control trials. This study serves as a basis for investigations of the effectiveness of BCW-based interventions. Fourth, we recommend replicating the study with a large sample, potentially using face-to-face interviews instead of an online survey. Such a replication study allows assessing the generalisability of the current study.

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CRediT authorship contribution statement

All authors: Conceptualisation, Methodology, Project administration **Annika Tensi:** Software, Formal analysis, Investigation, Writing - Original Draft, Writing – Review & Editing, Visualisation **Frederic Ang** and **H. J. van der Fels-Klerx:** Writing -Review & Editing, Supervision, Funding acquisition .

Declaration of competing interest

The authors declare that they do not have 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. Behaviour Change Wheel

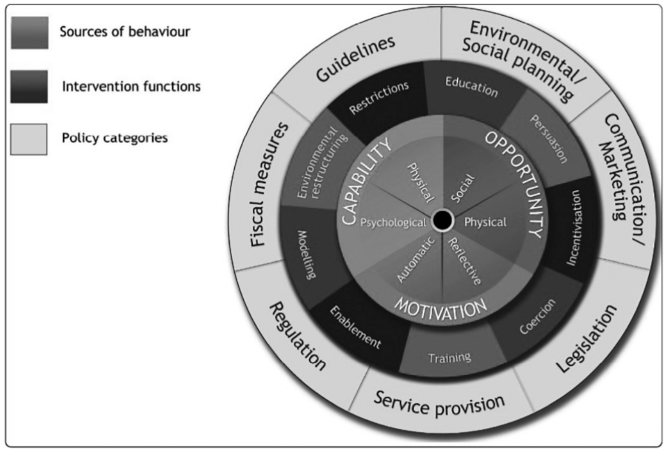

Figure Appendix A1. The Behaviour Change Wheel by Michie et al. (2011).

Appendix B. Summary statistics of general attitudes

We characterise our sample in terms of attitudes on innovations, the environment, climate change and soil quality. The farmers are somewhat worried regarding the effects of climate change and neutral towards a potential loss of soil quality. They take on average 3.3 specific measures to protect their soil quality. The most popular measure is to include cover crops in the crop rotation, which is practised by 92 % of the Dutch and 80 % of the German farmers in the sample. The farmers do not see themselves as generally open towards innovations or as innovators. We could therefore say that the sample is rather conservative. For a summary of the general attitude variables see table Appendix B1.

Table Appendix B1
Summary statistics of general attitude variables.

Statistic	N	Median	Mean	SD	Description
Concerns climate[a]	194	2	2.36	1.04	Concerns regarding effects of climate change on farm operations
Concerns soil quality[a]	194	3	2.88	1.15	Concerns regarding long term soil quality
Number of soil quality measures	196	3	3.28	1.21	Number of measures taking to maintain/improve soil quality
Openness to innovations[b]	195	2	2.83	1.20	Generally open towards adoption of technological innovations on the farm
Innovator[b]	195	2	2.21	1.21	Respondent considers him-self an innovator
Technological fix[c]	186	3	2.72	1.27	Confident that environmental problems can be solved in (cost) efficient way with new technologies

[a] Concern measured on five-point Likert scale, where 3 is considered a neutral response, higher values reflect unconcern, lower values worriedness with respect to the item.
[b] Agreement measured on a five-point Likert scale, where 3 is considered a neutral response, higher values reflect agreement and lower values disagreement.
[c] Confidence measured on five-point Likert scale, where 3 is considered a neutral response, higher values reflect confidence and lower values doubt.

Appendix C. Attitudes towards microbial applications

On average, 33 % of the participants indicate that they are making use of microbial applications, with almost no difference between the samples from Germany and the Netherlands. Overall, the participants are "somewhat unlikely" to adopt microbial applications (likelihood mean 2.01) despite their "somewhat positive" attitude towards microbial applications (attitude mean 3.74). Participants are rather pessimistic about the costs and benefits in terms of chemical and fertiliser reduction and yield and price premium increases. German farmers are more pessimistic in these domains, except for the price premiums, than Dutch farmers (see table Appendix C1 for further details).

Table Appendix C1
Descriptive statistics of attitudes and perceptions towards microbial application.

Statistic	Sample			The Netherlands			Germany		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Usage	195	0.33	0.47	133	0.32	0.47	62	0.35	0.48
Likelihood	128	2.01	1.13	90	2.07	1.19	38	1.87	0.99
Attitude	190	3.74	1.35	130	3.78	1.34	60	3.67	1.37
Costs	192	2.48	1.24	133	2.58	1.22	59	2.27	1.26
Chemicals	192	2.31	1.44	133	2.47	1.53	59	1.93	1.14
Fertilisers	191	2.36	1.42	132	2.58	1.54	59	1.88	0.93
Yield	192	1.73	0.90	133	1.74	0.96	59	1.73	0.74
Price	190	2.28	1.52	132	2.12	1.46	58	2.66	1.62

Appendix D. Kurtosis and skewness

Table Appendix D1
Kurtosis and skewness test.

COM-B main	Elements sub	Variable	Kurtosis	Skewness
Capability	Psychological	Understand	−1.2	−0.2
		Effect on plants	−1.2	−0.2
		Effect on soil	−1.1	−0.3
	Physical	Training needed	−0.6	0.6
		Machinery needed	−1.1	0.4
Opportunity	Physical	Purchase	−0.9	0.5
		Support	−1.1	0.2
	Social	Approval	−1.6	0.0
Motivation	Automatic	Trust Efficacy	1.1	1.1
		Trust Safety	−0.5	0.7
	Reflective	Soil health	−0.2	0.7
		Resistance	0.4	0.8
		Plant health	0.2	0.7
		Farmer health	1.4	1.5
		Consumer health	−0.2	1.1

Appendix E. Correlations COM-B elements

Table Appendix E1
Correlation matrix COM-B variables.

	Underst....	Plants	Soil	Train.	Machi.	Funds.	Purch.	Supp.	Approv.	TrustEff.	TrustSaf	SoilH	Resist	PlantH.	FarmerH.	ConsumH.
Understand	1	0.70	0.66	0.39	0.13	0.26	0.20	0.17	0.11	0.18	0.18	0.14	0.21	0.24	0.12	0.11
Effect on plants	0.70	1	0.84	0.29	0.15	0.18	0.18	0.23	0.14	0.09	0.17	0.09	0.14	0.10	0.11	0.11
Effect on soil	0.66	0.84	1	0.25	0.14	0.21	0.10	0.20	0.14	0.10	0.15	0.15	0.17	0.13	0.07	0.13
Training needed	0.39	0.29	0.25	1	0.44	0.45	0.37	0.31	0.26	0.33	0.36	0.24	0.14	0.26	0.16	0.23
Machinery needed	0.13	0.15	0.14	0.44	1	0.44	0.21	0.24	0.35	0.23	0.17	0.16	0.16	0.19	0.23	0.24
Funds needed	0.26	0.18	0.21	0.45	0.44	1	0.36	0.26	0.29	0.36	0.33	0.29	0.25	0.36	0.18	0.32
Purchase	0.20	0.18	0.10	0.37	0.21	0.36	1	0.30	0.15	0.31	0.26	0.17	0.08	0.22	0.08	0.22
Support	0.17	0.23	0.20	0.31	0.24	0.26	0.30	1	0.23	0.22	0.23	0.05	0.02	0.10	0.07	0.13
Approval	0.11	0.14	0.14	0.26	0.35	0.29	0.15	0.23	1	0.15	0.21	0.03	0.06	0.10	0.22	0.27
Trust efficacy	0.18	0.09	0.10	0.33	0.23	0.36	0.31	0.22	0.15	1	0.52 1	0.51	0.51	0.60	0.23	0.25
Trust safety	0.18	0.17	0.15	0.36	0.17	0.33	0.26	0.23	0.21	0.52	0.37	0.37	0.35	0.44	0.26	0.24
Soil health	0.14	0.09	0.15	0.24	0.16	0.29	0.17	0.05	0.03	0.51		1	0.67	0.69	0.20	0.24
Resistance	0.21	0.14	0.17	0.14	0.16	0.25	0.08	0.02	0.06	0.51	0.35	0.67	1	0.75	0.23	0.13
Plant health	0.24	0.10	0.13	0.26	0.19	0.36	0.22	0.10	0.10	0.60	0.44	0.69	0.75	1	0.25	0.20
Farmer health	0.12	0.11	0.07	0.16	0.23	0.18	0.08	0.07	0.22	0.23	0.26	0.20	0.23	0.25	1	0.51
Consumer health	0.11	0.11	0.13	0.23	0.24	0.32	0.22	0.13	0.27	0.25	0.24	0.24	0.13	0.20	0.51	1

Appendix F. Correlations COM-B sub-elements

Table Appendix F1
Correlation matrix of COM-B elements and sub-elements.

	C	M	O	C.psy	C.phy	M.aut	M.ref	O.phy	O.soc
C	1	0.728	0.990	0.562	0.984	0.696	0.584	0.981	0.610
M	0.728	1	0.653	0.326	0.690	0.991	0.915	0.621	0.290
O	0.990	0.653	1	0.589	0.993	0.616	0.510	0.979	0.597
C.psy	0.562	0.326	0.589	1	0.519	0.285	0.290	0.558	0.298
C.phy	0.984	0.690	0.993	0.519	1	0.654	0.547	0.961	0.563
M.aut	0.696	0.991	0.616	0.285	0.654	1	0.863	0.589	0.271
M.ref	0.584	0.915	0.510	0.290	0.547	0.863	1	0.471	0.201
O.phy	0.981	0.621	0.979	0.558	0.961	0.589	0.471	1	0.557
O.soc	0.610	0.290	0.597	0.298	0.563	0.271	0.201	0.557	1

Appendix G. Supplementary data

Supplementary data and code and the original survey to this article can be found online at OSF (DOI: 10.17605/OSF.IO/EY5SD) and https://doi.org/10.1016/j.techfore.2022.121825.

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