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Autonomous agriculture in public perception - German consumer segments' view of crop robots

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ABSTRACT

Public acceptance of agricultural technologies is an important determinant of their success. In the case of autonomous crop robots, recent research from Germany suggests that societal acceptance of the technology plays an important role for farmer acceptance of crop robots. Yet little research has been conducted so far into how the public perceives autonomous agricultural technologies like crop robots. Investigating the public's opinion on crop robots will provide answers to one of farmers' questions in the decision to invest in crop robots. Through consumer segmentation and hypotheses-based characterization, specific consumer groups with differing attitudes towards crop robots are identified. Two discrete choice experiments on digital and autonomous methods of weed management (n = 675) and tractor size and degree of autonomy (n = 645), conducted as part of a larger representative consumer survey in Germany (n = 2,012), are submitted to a Hierarchical Bayes estimation and subsequent latent class analysis. The identified consumer segments are characterized in a hypotheses-based approach with hypotheses centering on consumer attitudes measured as 5-point Likert-type items and as spontaneous image associations. Both subsamples can be segmented into three groups, which are comparable between the experiments in their socio-economic composition. Results suggest that the German public is largely positively inclined towards autonomous agricultural technologies. The method of weed control is considered more important than the vehicle type (i.e., conventional tractor or crop robot) and vehicle size is considered more important than degree of autonomy. Only the respective smallest consumer segments in the two experiments indicate indifference or a more conservative perspective. Participants' attitude towards environmental preservation appears to have a positive influence on their evaluation of autonomous agricultural technologies. To the authors' best knowledge, this is the first investigation into the public opinion of crop robots, based on a large sample representative of the German population in four socio-demographic variables. It indicates that the German population is most interested in the reduction of agrochemicals in plant production and will also accept autonomous agricultural technologies to achieve this goal. Policymakers should make use of these insights when communicating about novel technologies in agriculture and extension agents should relay this information to farmers, particularly those already interested in investing in crop robots.

1. Introduction

Digital and autonomous farming equipment show the potential to change the economic, environmental, and social dimensions of food production (Basso & Antle, 2020; van der Burg et al., 2022). Particularly the use of robots in crop production may result in noteworthy changes to the economies of scale in arable farming (Lowenberg-DeBoer et al., 2021). As the cultivation of smaller plots becomes more profitable, agro-ecological systems may benefit from higher crop diversity. Crop robot-associated technologies like spot-spraying or hoeing may reduce the amount of agro-chemicals applied and potentially leaching into the environment (Bongiovanni & Lowenberg-DeBoer, 2004). If combined

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with small, low-weight machines, the effects of soil compaction on soil biota and structure may be alleviated (Shockley et al., 2019). Labor-intense processes like manual weeding, especially relevant in organic farming, may be decoupled from human working hours (Sørensen et al., 2005), again increasing profitability of production. Investment decisions for or against crop robots are influenced by the expected societal reaction, among other monetary and non-monetary factors (Rübcke von Veltheim et al., 2021; Spykman et al., 2021a). This points to a potential barrier to farm-level application of crop robots: the approval of society is a critical building block for the dissemination of crop robots in quest of a more sustainable agricultural system.

1.1. Public perception of agricultural technology developments

In the past, public perception of controversial technologies was frequently investigated only after society had already voiced apprehension or rejection (Gupta et al., 2012). For example, experience with the introduction of genetic engineering to agriculture highlighted the decisive role of public opinion, as it resulted highly restricted use or outright ban of genetically modified organisms (GMOs) in Europe (Gaskell et al., 2000). Food nanotechnology as applied to both packaging and the food itself has also been discussed controversially as consumers worried about the perceived risk–benefit balance as well as 'naturalness' of the food products and companies' intentions regarding profit and consumer benefit. However, application of this technology to packaging rather than food appears more acceptable to consumers (Giles et al., 2015). In dairy production, a sector of agriculture more complex due to the dimension of animal welfare but also more advanced in automation than crop production, milking robots are met with rather positive attitudes (Henchion et al., 2022), although attitudes towards 'modern dairy farming' vary between societal groups (Boogaard et al., 2011). It appears that consumers differentiate clearly whether a novel technology affects the food directly or only the processes surrounding its production. It is still to be determined, however, whether the trajectory of robots in crop production will follow the same path of societal acceptance. The European population appears not to view robots in agriculture as a priority (Eurobarometer, 2014), yet the perspective may have been changed by market developments since the survey was administered. Concerns about robots in agriculture in general may relate to their impact on the labor market, ranging from job loss due to replacement of unskilled labor (cf. Sparrow & Howard, 2021) to an increase in opportunities for technically skilled employees (Ofori & El-Gayar, 2021), the so-called job polarization phenomenon (Marinoudi et al., 2019). Additionally, digital farming technologies have raised concerns about negative impacts on farmer-consumer relationships in short food supply chains (Lioutas & Charatsari, 2020), which could also apply to crop robots.

Given the potentially disruptive impact of autonomous equipment in agriculture and the sector's continued focus on economic and environmental evaluations, Rose and colleagues advocate for applying a multi-actor approach to agricultural technology evaluation for a sustainable adoption process grounded in all three dimensions of sustainability, including social impacts (Rose et al., 2021; Rose & Chilvers, 2018). Along the same lines, Klerkx et al. (2019) identify society's interests in digital agricultural technologies as an emerging question on the social science research agenda, and Jacquet et al. (2022) call to include socio-economic aspects in the development of solutions for pesticide-free agriculture. If societal concerns are duly acknowledged before the ubiquitous deployment of robots in primary food production, public rejection may be preempted by providing objective information.

In Germany, society's attitude towards agriculture and food production is complex. German consumers value the 'naturalness' and safety of their food highly (Román et al., 2017), which played into their heterogeneous attitudes toward GMOs (Emberger-Klein et al., 2016), nanotechnology (Roosen et al., 2015), and agro-chemicals (Salamon et al., 2014; Zander et al., 2013). Organic certification, for example, can act as a proxy for 'naturalness', but the relative importance of this attribute differs by product group, availability, convenience, and price (Schäufele & Janssen, 2021). Influential newspapers in Germany tend to frame 'naturalness' positively but frame productivity predominantly negatively (Kayser et al., 2011). This raises the question how the public image of crop robots may develop, particularly as the media is named one of the strongest sources of perceived external pressure by farmers (Ermann et al., 2017). However, recent research suggests that general media outlets portray digital and autonomous agriculture rather positively, both nationally (Mohr & Höhler, 2021) and internationally (Javaheri et al., 2020; Ofori & El-Gayar, 2021). Pfeiffer et al. (2021) studied directly the German public acceptance of digitalization in agriculture, finding that society responds favorably to digital farming technologies, valuing their potential to reduce the environmental impact of agriculture and improve farmer well-being. Additionally, a comparison of participants' spontaneous associations with images of small and large autonomous crop robots during sowing showed that small swarm robots are viewed more positively than large autonomous tractors, which the authors attribute to safety and environmental concerns (Pfeiffer et al., 2021). However, not all of these potential determinants of societal acceptance exert an equal influence on controversial technologies (Gupta et al., 2012). The present analysis therefore aims to contribute to the currently sparse body of literature on public acceptance of crop robots.

1.2. Objectives and hypotheses

While the public are not the end users of crop robots, they are important stakeholders in the system. The agricultural sector in many countries depends – to varying extents - on public money. Therefore, public preferences for or against crop robots may influence their deployment in primary food production. Consumer choice may be pursued as one way of eliciting these public preferences. Based on two discrete choice experiments (DCE) conducted as part of the same representative survey from which Pfeiffer et al. (2021) drew their data, the public perception of crop robots is thus assessed using a preference-focused method. DCE have been used to evaluate public preference for certain production methods, e.g., following organic standards (Schäufele & Hamm, 2017) or using GMOs (Emberger-Klein et al., 2016). Presently, however, this method has not been applied in the context of public preferences of digital or autonomous agricultural technologies. The analysis of these two experiments is carried out in a hypotheses-based manner and uses Latent Class Analysis (LCA) to identify consumer segments with relative preferences for specific characteristics of crop robot technology as well as socio-economic and attitudinal properties.

Society's opinion on crop robots may be influenced by different factors, including the environment, farmers' wellbeing, and attitudes towards technology use. An important construct is the increased distance of the general public from practical agriculture, which is associated with a rejection of large, increasingly automated farm businesses (Salamon et al., 2014; Zander et al., 2013). Conversely, farmers are deterred from investing in crop robots by a fear of creating an alienated image of agriculture, but are motivated by expectations of simplified work routines (Spykman et al., 2021a). Previous research, however, draws an inconclusive picture of society's perception of farmer workload relative to their income (Rübcke von Veltheim et al., 2019; Salamon et al., 2014; Zander et al., 2013). It is therefore hypothesized that perception of digital technologies as alienating as well as a preference for family farming structures correspond to a preference for conventional technologies. Conversely, if consumers agree that farmers face a high workload, they are expected to prefer vehicles with a certain degree of autonomy. Further, a proclaimed fear of modern agricultural machines is expected to influence the preferences for vehicle types with regard to both size and degree of autonomy, analogous to the influence of different fears on the acceptance of automatically driving vehicles in

Table 1
Distribution of socio-demographic variables in the population, the total sample, and the two subsamples (no significant differences according to Pearson Chi^2 Test of Independence: $p < 0.05$).

		Population *	Total sample	Experiment A - Weed Management	Experiment B - Autonomous Tractors
Size		51.6 million	2,012	675	645
		Shares in %			
Sex	Female	48.4	50.2	51.6	49.1
	Male	51.6	49.8	48.4	50.9
Age	< 40 years	37.0	35.0	36.9	33.5
	≥ 40 years	63.1	65.0	63.1	66.5
Level of education	No university entrance qualification ('Abitur')	63.2	63.0	62.7	60.6
	University entrance qualification ('Abitur') or higher	36.9	37.0	37.3	39.4
Size of place of residence	< 5,000 inhabitants	14.0	14.1	15.3	13.5
	5,000–100,000 inhabitants	53.0	53.4	51.6	54.0
	> 100,000 inhabitants	33.1	32.5	33.2	32.6
Work experience in agriculture or related sector**	Yes	n/a	8.2	7.3	8.2
	No	n/a	91.8	90.7	91.8
Farmers in personal network (acquaintances or relatives)**	Yes, with conversations about agricultural topics	n/a	19.2	18.1	20.3
	Yes, without conversations about agricultural topics	n/a	14.2	12.0	14.9
	No	n/a	66.6	69.9	64.9

* based on the report "Markt Media Analyse b4p 2017 III Märkte + Menschen" for German residents at least 18 years of age and with access to the internet.
** these variables were not compared between the population and the total sample.

general (Golbabaei et al., 2020).

Given the potential of crop robots to improve the environmental sustainability of agriculture, participants' environmental attitudes are of interest. The use of herbicides is met with more negative public attitudes than mechanical weed control (Lehberger & Becker, 2021; Römer et al., 2019). On the other hand, little is known about public attitudes toward the problem of soil compaction due to heavy agricultural equipment as consumer studies focus on the use of agro-chemicals or GMOs and summarize further aspects under "environmentally-friendly production" (Sidali et al., 2016). Therefore, it is hypothesized that consumers supporting environmental preservation prefer methods of weed control reducing the use of herbicides as well as small vehicle sizes.

Not all opinions on digital agricultural technologies may be fully rational, as has been shown in a comparison of implicit and explicit associations with different methods of crop protection (Römer et al., 2019). For the present study, it is of interest whether such a discrepancy may also be observed between spontaneously formed associations and somewhat more reasoned choices. It is therefore expected that consumers with positive spontaneous associations with images of crop robots prefer digital and autonomous technologies.

Based on these hypotheses, comparable socio-economic compositions of the two subsamples, and the strong relationship between the two experiments' attributes, the results of the two DCE analyses will be interpreted jointly. This concept aims to (1) provide information on the German public's general opinion on crop robots, (2) identify distinct consumer segments with different preferences that may need to be addressed differently, and (3) determine which attitudes influence crop robot support or rejection. Understanding society's opinion on crop robots may prove particularly useful to policymakers aiming to promote digital and autonomous technologies in agriculture.

2. Material and methods

2.1. Data collection and preparation

The data were collected in a national online survey among the German adult population with internet access in 2018. The sample was obtained through a professional field service provider, allowing for preselected quotas to ensure representativeness regarding age, sex, level of education, and size of place of residence (Table A1). The survey resulted in 2,012 valid datasets. The questionnaire contained questions on socio-demographic characteristics, self-assessed knowledge about agricultural processes, attitude toward the environment and various aspects of agriculture, and support for specific technologies (recorded on five-point Likert-type scales). It further comprised three DCE and four spontaneous image association tasks on autonomous technologies in crop and dairy production. With the exception of the DCE, the survey results have been published in Pfeiffer et al. (2021), who provide more detailed information on the structure of the questionnaire and data manipulation before analysis.

The participants' spontaneous associations with the two images relevant to the present analysis (small swarm robots (AGCO GmbH, 2017) and large autonomous tractor (CNH Industrial America LLC, 2016)) required numerical encoding to be included in the analysis. The resulting spontaneous image association (SIA-) score is used in the analysis to uncover potential differences between emotional and rational responses: DCE elicit more reasoned responses (Bettman et al., 1998; Shafir et al., 1993) whereas images are known to stimulate affective responses based on emotions and feelings (Collier, 1957; Harper, 2002). In the survey, each participant was allowed to submit up to three spontaneous statements for each image, which were subsequently classed as positive, neutral or negative (Pfeiffer et al., 2021). For the present analysis, a value of +1 for positive, 0 for neutral, and −1 for negative associations was assigned. Statement options left empty or not clearly definable were treated as neutral. Each participant was thus assigned a SIA-score ranging from −3 to +3. While this approach reduces the information, previous research has similarly recorded image associations on a scale between opposing words (Busch et al., 2019) or on a positive–negative scale (Kühl et al., 2019). For the analysis, only a general tendency for each image, analogous to the Likert-type scales, is required.

2.2. Set-up of the discrete choice experiments

The three DCE focused on (digital) alternatives for weed management in arable farming, size and degree of autonomy of equipment for arable farming, and use of robots and sensors in dairy production, respectively. Each survey participant completed only one of the three DCE, which were assigned randomly, producing three roughly equal subsamples. The present analysis considers only the DCE on methods of

Table 2
Overview of attributes and respective levels for the two experiments.

	Experiment A - Weed Management			Experiment B - Autonomous Tractors		
	Method of weed control	**Vehicle type**	**Price increase of wheat flour**	**Degree of autonomy**	**Vehicle size**	**Price increase of wheat flour**
Level 1	Conventional spraying	Conventional tractor	None 0.35€/kg	Conventional; human-driven	Currently available equipment	None 0.35€/kg
Level 2	Spot-spraying	Large autonomous tractor	Moderate 0.50€/kg	Partially autonomous; on-site remote supervision or steering	Smaller than current equipment	Moderate 0.50€/kg
Level 3	Hoeing	Small swarm robots	Strong 0.65€/kg	Fully autonomous; no supervisor on-site	Larger than current equipmen	Strong 0.65€/kg

weed management (n = 675) and degree of autonomy (n = 645) in crop production. The third DCE on sensors in dairy production has already been analyzed in comparison to the experiment on methods of weed management (Spykman et al., 2021b). The distribution of sociodemographic variables does not differ significantly between the population and the total sample, between the total sample and the subsamples, and between the two subsamples, respectively (Chi^2 Test of Independence: $p < 0.05$). Table 1 summarizes the sociodemographic composition of these four levels of data.

The experiments each contained three attributes, which were each subdivided into three attribute levels (Table 2). The attributes were chosen based on expert judgement of the most relevant field of application of crop robots at the time of the survey (weed control), technological properties of crop robots visible to consumers (vehicle size and degree of autonomy), and price increments of a standard consumer product in relation to its consumer price at the time of the survey (price of one kilo of wheat flour). Since survey participants themselves are not potential users of the presented technologies, their valuation of the technology's properties had to be contextualized, which was achieved by introducing the consumer price attribute. The meaning of the attributes was presented to participants using pictograms and brief descriptions introduced before the respective experiment. In both experiments, technology attributes of level 1 represent conventional, i.e., non-digital or autonomous technologies. Levels 2 and 3 indicate increasing distance from conventional technologies through digitalization and/or autonomation. For example, in Experiment A, both spot-spraying and hoeing are presented as being camera-supported and thus digital, but spot-spraying still relies on herbicides. The attribute levels were combined into choice cards based on balanced overlap design to produce a fixed choice set, i.e., every participant in an experiment was presented the same choice cards in the same order. In nine repetitions, participants were asked to select the most attractive option from three choice cards or a 'none'-option.

The attribute 'vehicle type' in experiment A relates to the attributes 'degree of autonomy' and 'vehicle size' in experiment B, allowing for a certain degree of comparability between the two experiments. Given the lack of statistical differences between the two subsamples, a comparison and synthesized conclusion is attempted after the individual analysis of the two experiments.

2.3. Analysis

The application of DCE to stated preferences or hypothetical choices, in which participants are not the actual users of the technology investigated, was pioneered by Louviere and Woodworth (1983) and is based on the concept of dimensionless utility derived from product attributes determining product preferences (Lancaster, 1966; McFadden, 1974). Latent utilities may be inferred from the analysis of measurable items (Louviere et al., 2010) and are thus comparable between real and hypothetical choices. DCE have since been frequently applied to elicit stated preference in various disciplines.

The data of the DCE were first submitted to a Hierarchical Bayes (HB) estimation, which consists of two models in a hierarchical structure and draws on the Bayesian Theorem of conditional probabilities. The upper-level model initially assumes a multivariate normal distribution for participants' part-worth utility values. Subsequently, the lower-level model considers the results of the upper-level model and assumes that participants' choices for specific attribute levels underly a multinomial logit model. The relevant parameters of the assumed multivariate normal distribution are then estimated through Monte Carlo Markov Chain iterations. Convergence of parameter values and calculation of final part-worth utility values for participants tends to be based on several thousand iterations and may thus be considered robust (Sawtooth Software Inc., 2016).

Following the HB estimation for each subsample, a latent class analysis (LCA) was conducted, in which individuals are grouped, or segmented, based on their response patterns. In a first step, the desired range of segments is entered, and random estimates of the segments' utility values are made. Next, the probability of each participant belonging to each possible segment is calculated and used as weights to produce log-likelihood values for the assignments. This process is iterated until the log-likelihood converges and participants are thus grouped into the segment with the highest probability value. The reported part-worth utility values for the segments correspond to the average of the constituent participants' part-worth utility values. The optimal number of segments for further analysis is determined based on multiple fit criteria (e.g., Aikake information criterion (AIC), Bayesian information criterion (BIC), Log-Likelihood) (Sawtooth Software Inc., 2019). The fit criteria's individual performance in Monte-Carlo simulation studies varies with sample size (Morgan, 2015; Nylund et al., 2007), but evaluation of their relative changes in response to changes in the number of segments can be used to find the best-fitting model (Nylund-Gibson & Choi, 2018). As even joint consideration of these criteria may not always allow for conclusive determination of one optimal solution, analysis of all candidate solutions to select the best interpretable one is advised (Nylund-Gibson & Choi, 2018; Swait, 1994). This approach was applied in the present analysis as the fit criteria improved markedly from two to three and three to four-segments in both experiments. To compare utilities between segments, the values are rescaled using zero-centered differences. The results allow for a comparison of relative weighting of the attributes in the choice process and relative preferences for specific manifestations of the attributes between the segments (Sawtooth Software Inc., 2019). The HB and LCA analyses were carried out in Lighthouse Studio 9.5.3. (Sawtooth Software Inc., 2017).

The LCA results indicating the most likely segment for each participant were subsequently transferred to SPSS 26 (IBM Corp., 2019) for the analysis of socio-economic and attitudinal differences between segments. Pearson's Chi^2 Test of Independence was applied to compare distributions of socio-economic characteristics between the segments. The results of this test also include the effect size Cramér's V, which suggest a meaningful influence of the independent variable above a threshold value of 0.2. The attitudinal profile was produced by analysis of five attitudinal variables recorded on five-point Likert-type scales (1 = fully disagree, 2 = rather disagree, 3 = undecided, 4 = rather agree, 5 = fully agree) and spontaneous associations with two images of crop

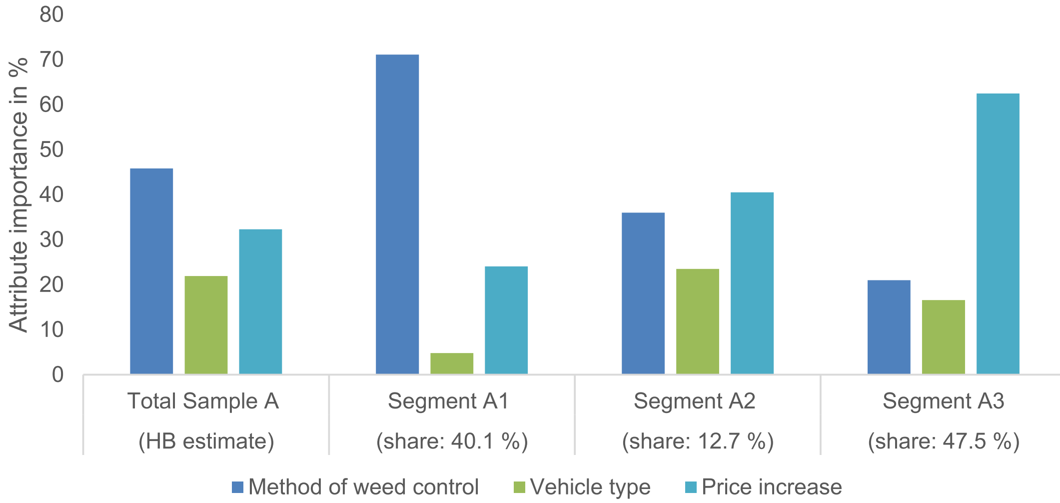

Fig. 1. Attribute importance for total sample and segments of Experiment A (n = 675) in % (adapted from Spykman et al. (2021b)).

Table 3
Part-worth utility values of attribute levels for Experiment A (n = 675) (adapted from Spykman et al. (2021b)).

			Segment A1	Segment A2	Segment A3
Attribute level part-worth utility (zero-centered dfiferences)	**Method of weed control**	Conventional	−112.34	−54.00	−9.30
		Spot-spraying	11.33	0.00	36.12
		Hoeing	101.01	53.99	−26.82
	Vehicle type	Conventional	−5.00	37.93	23.61
		Autonomous	−4.45	−5.42	2.46
		Small swarm robots	9.45	−32.51	−26.07
	Price increase	None	33.93	77.19	79.49
		Moderate	4.35	−32.82	28.41
		Strong	−38.28	−44.37	−107.89
	'None'-option		−4.27	249.35	−490.02

robots (seven-point SIA-score, see section 2.1) using the Kruskal-Wallis H Test. This non-parametric test compares the central tendencies of multiple independent samples (i.e., the segments) and was chosen because the Likert-type scales and SIA-scores are not normally distributed (Shapiro-Wilk Test: $p < 0.001$). If the Kruskal-Wallis H-test yields a significant outcome, the Dunn-Bonferroni post-hoc test conducts pairwise comparisons using Bonferroni-corrected significance thresholds. This combination of tests for descriptive variables of different data types is not uncommon in the description of latent class segments (e.g., D'Addezio et al., 2015).

The following five attitudinal variables were included in the analysis: "Digital farming technologies alienate the farmer from his/her soil or animals", "Family farming structure seem valuable and should be preserved", "I am scared of modern agricultural machines", "Farmers should have more leisure time", and "I consider the preservation of the environment for future generations very important". Whereas Pfeiffer et al. (2021) conducted their analysis using factor values for Likert-type scales, not individual items, the present analysis will focus on correlations between segments and individual variables to reap items' individual informative value. The relevance of these items as well as the SIA-scores for public evaluation of crop robots was tested through hypotheses, which were evaluated in a qualitative manner under consideration of the correlational test results from both experiments. The following hypoptheses were tested:

- H1: Consumer segments who agree that digital farming technologies lead to alienation of the farmer from his/her land or animals prefer conventional technologies.
- H2: Consumer segments who agree that family farming structures seem valuable and should be preserved prefer conventional technologies.
- H3a: Consumer segments who indicate to be scared of modern agricultural machines prefer conventional tractors over large autonomous tractors in Experiment A.
- H3b: Consumer segments who indicate to be scared of modern agricultural machines prefer small tractors over large or conventional tractors sizes in Experiment B.
- H4: Consumer segments who agree that farmers should have more leisure time prefer fully autonomous tractors over partially autonomous tractors and both types over human-driven tractors in Experiment B.
- H5a: Consumer segments who agree that they consider preservation of the environment for future generations very important prefer hoeing over spot-spraying and both digital technologies over conventional weed control in Experiment A.
- H5b: Consumer segments who agree that they consider preservation of the environment for future generations very important prefer small tractors in Experiment B.
- H6: Consumer segments with a positive SIA-score on the image of small swarm robots prefer digital and autonomous technologies.
- H7: Consumer segments with a positive SIA-score on the image of a large autonomous tractor prefer digital and autonomous technologies.

3. Results

In both experiments, the fit criteria (AIC, BIC, Log-Likelihood) suggested three- and four-segment solutions as appropriate. The improvements in these criteria from two to three and three to four segments, respectively, were similarly large. For this reason, the three- and four-segments solutions were screened for interpretability (cf. Swait, 1994). Both times, the respective three-segment solution proved to be best

Table 4
Socio-demographic composition of segments in Experiment A (n = 675).

		A1	A2	A3	Chi^2	df	p	Cramér's V
		Shares in %						
Sex	Male	47.3	49.4	49.2	0.24	2	0.889	0.019
	Female	52.7	50.6	50.8				
Age	< 40 years	38.2	26.5	38.5	4.39	2	0.111	0.081
	≥ 40 years	61.8	73.5	61.5				
Level of education (**)	No Abitur	55.8	74.7	65.7	12.00	2	0.002	0.133
	Abitur or higher	44.2	25.3	34.3				
Size of place of residence	< 5,000 inhab.	14.5	15.7	15.9	7.10	4	0.131	0.103
	5,000–100,000 inhab.	48.8	44.6	56.0				
	> 100,000 inhab.	36.7	39.8	28.2				
Experience in agric. or related sector (***)	Yes	3.9	2.4	11.7	16.53	2	0.000	0.156
	No	96.1	97.6	88.3				
Farmers in personal network (***)	Yes, we discuss farming-related topics	15.5	7.2	23.3	24.17	4	0.000	0.189
	Yes, but we do not discuss farming-related topics	10.2	6.0	15.2				
	No	74.2	86.7	61.5				

Pearson Chi^2-Test of Independence: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5
Attitudinal profiles of segments in Experiment A (n = 675).

	Seg-ment	Median	Likert-type scale				
			Fully disagree	**Rather disagree**	**Unde-cided**	**Rather agree**	**Fully agree**
			Shares in %				
Digital farming technologies alienate the farmer from his/her land or animals.	A1[a]	undecided	6.0	30.4	35.3	22.6	5.7
	A2[a]	undecided	4.8	22.9	42.2	25.3	4.8
	A3[a]	undecided	9.4	22.9	42.2	14.9	6.5
Family farming structures seem valuable and should be preserved. (***)	A1[a]	fully agree	0.0	0.4	6.0	39.9	53.7
	A2[b]	rather agree	3.6	0.0	16.9	50.6	28.9
	A3[c]	rather agree	0.6	1.0	12.3	41.7	44.3
I am scared of modern agricultural machines. (*)	A1[a]	rather disagree	26.5	44.9	16.6	10.2	1.8
	A2[b]	rather disagree	16.9	36.1	38.6	3.6	4.8
	A3[a, b]	rather disagree	25.9	38.5	20.1	11.0	4.5
Farmers should have more leisure time. (***)	A1[a]	rather agree	0.4	2.1	23.3	53.7	20.5
	A2[b]	rather agree	3.6	1.2	43.4	33.7	18.1
	A3[a]	rather agree	0.6	1.9	25.9	45.6	25.9
I consider the preservation of the environment for future generations very important. (***)	A1[a]	fully agree	0.4	0.4	4.6	31.1	63.6
	A2[b]	rather agree	2.4	2.4	9.6	49.4	36.1
	A3[b]	fully agree	1.0	1.6	8.1	39.2	50.2

Kruskal-Wallis H-Test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Dunn-Bonferroni post-hoc Test:[a, b, c] segments with the same superscript do not differ significantly from each other.

interpretable and was therefore selected for further analysis. Experiment A has already been analyzed to some extent in Spykman et al. (2021b), but will be described in detail to provide a complete overview of the present analysis.

3.1. Experiment A

3.1.1. Segmentation results

Relative to the whole subsample, the segments identified in Experiment A reveal distinguishing patterns in attribute importance (Fig. 1). Segment A1 (41.1 %) is characterized by the strong weight given to 'method of weed control' (71.1 %) compared to both the full sample and the other two segments. Segment A2 comprises the lowest share of participants (12.7 %) and differentiates less between the attributes: 'price increase' (40.5 %) weighs only slightly stronger than 'method of weed control' (36.0 %), and the relative drop in importance of the attribute 'vehicle type' (23.5) is lower than in Segment A1 (4.8 %). Segment A3 as the largest segment (47.2) prioritizes the attribute 'price increase' (62.5 %) and ranks 'method of weed control' and 'vehicle type' almost equally low in importance (21.0 % and 16.6 %, respectively).

The part-worth utilities for the attribute levels indicate the different relative preferences for the options within each attribute between the segments (Table 3). Members of Segment A1 object to conventional weed management, showing strong utility increases from spot-spraying and especially hoeing. Although 'vehicle type' is comparatively unimportant to this segment, its members show a slight preference for small swarm robots. They may also be described as the least price sensitive, as shown by the small decreases in utility with increasing price levels. Participants in Segment A2 follow the same preference pattern for 'method of weed control', although at a lower magnitude corresponding to the attribute's lower importance to this segment. This segment's preference for conventional tractors over large autonomous tractors and small swarm robots again needs to be viewed in the context of low overall importance of 'vehicle type'. It is also rather price sensitive, showing the strongest decrease in utility from no to moderate price increase of all three segments while also considering 'price increase' the most important attribute. Last, the high positive utility of the 'none'-option suggests that participants in this segment frequently consider none of the presented choice cards an attractive option. This observation contrasts with the strongly negative utility derived from the 'none'-option by Segment A3, suggesting that segment members frequently considered one of the choice cards more attractive than the 'none'-

Table 6
SIA-score profiles of segments in Experiment A (n = 675).

	Seg-ment	Median	SIA-Score						
			−3	−2	−1	0	1	2	3
			Shares in %						
'small swarm robots' (***)	A1[a]	0	1.4	3.5	12.7	34.6	20.5	17.0	10.2
	A2[b]	0	0.0	6.0	12.0	60.2	18.1	2.4	1.2
	A3[a]	0	1.0	3.9	9.7	41.7	25.9	10.7	7.1
'large autonomous tractor' (**)	A1[a, b]	0	3.9	3.5	15.9	33.2	22.3	11.7	9.5
	A2[a]	0	2.4	1.2	13.3	62.7	14.5	2.4	3.6
	A3[b]	0	1.6	2.9	11.0	37.9	26.2	14.2	6.1

Kruskal-Wallis H-Test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Dunn-Bonferroni post-hoc Test: [a, b] segments with the same superscripts do not differ significantly from each other.

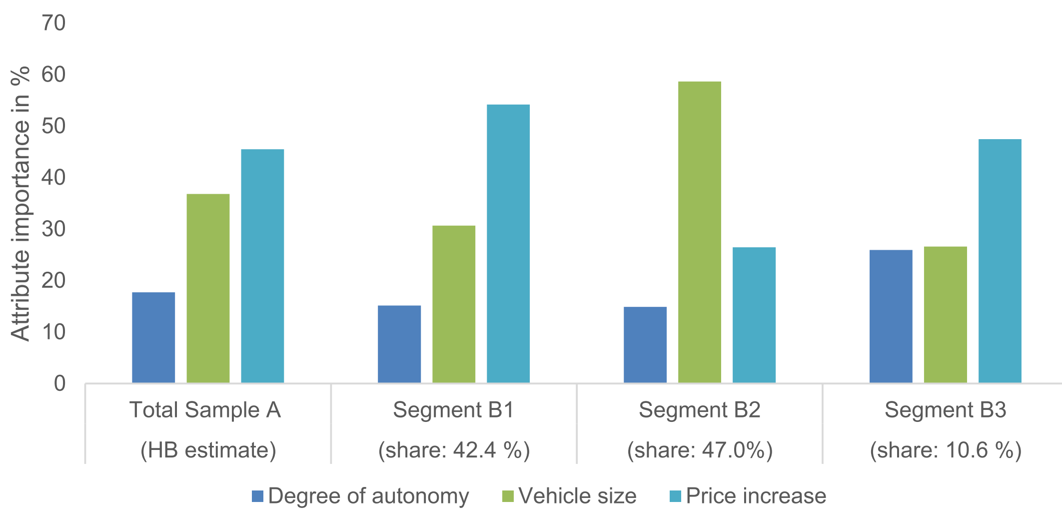

Fig. 2. Attribute importance for total sample and segments of Experiment B (n = 645) in %.

option. Segment A3 also considers price increase the most important attribute. Unlike Segment A2, however, this segment derives positive utility from moderate price increases, suggesting tolerance thereof, but also shows the strongest drop in utility from moderate to strong price increases. Participants in this segment reject small swarm robots and prefer conventional tractors, again with the reservation of low overall importance of the attribute 'vehicle type'. Regarding the attribute 'method of weed control', Segment A2 stands out as the only segment deriving lower utility from hoeing than from spot-spraying while also showing the lowest decrease in utility for conventional weed management compared to spot-spraying.

3.1.2. *Segment description*

In their socio-economic composition, the segments differ significantly from each other regarding level of education, work experience in farming or related fields, and farmers in their personal networks (Table 4). Segment A1 shows the highest rate of individuals with higher levels of education and the second lowest rate of both work experience and personal connections working in farming. Segment A2 comprises a similar percentage of individuals without work experience in farming, but also a much smaller percentage of higher levels of education or personal connections to the agricultural sector. In this regard, both segments differ strongly from Segment A3, whose members claim the highest rates of work experience and personal connections working in farming. They rank between the other two segments with respect to higher levels of education.

The attitudinal profiles (Table 5) provide insight into the different motivations and opinion of the segments' members in terms of agreement to Likert-type items and image association. The detailed test results are reported in the appendix (Table A2). The segments differ significantly on all statements except 'Digital farming technologies alienate the farmer from his/her land or animals'. Segment A1 shows significantly higher agreement than one or both other segments, respectively, to the statements regarding preservation of family farms, increased leisure time for farmers, and preservation of the environment. This segment agrees significantly less often to fear modern agricultural machines. Segment A2, on the other hand, shows a higher rate of disagreement or indecisiveness on the statement of fear of modern agricultural machines. This group of participants shows the highest rates for the response option 'undecided' for all statements tested.

The distribution of the SIA-scores strengthens the claim that Segment A2 comprises the most indifferent participants (Table 6). Members of this segment are undecided more often than one or both other segments, respectively, on both images. Conversely, Segments A1 and A3 show somewhat more differentiated image associations with a clearly positive tendency.

3.2. *Experiment B*

3.2.1. *Segmentation results*

The segments in Experiment B also provide distinguishable patterns of attribute prioritization compared to the total sample (Fig. 2). Segment B1 comprises the second-largest number of participants (42.4 %) and is characterized by high importance given to the price attribute (54.2 %) and clear differentiation between the technical attributes 'degree of autonomy and 'vehicle size' (15.2 % and 30.7 %, respectively). Segment B2, which is somewhat larger than B1 (47.0 %), considers 'vehicle size' by far the most important attribute (58.7 %), assigning less than half the importance to the attributes 'price increase' (26.6 %) and especially 'degree of autonomy' (14.9 %). Segment B3, finally, represents a small

Table 7
Part-worth utility values of attribute levels for Experiment B (n = 645).

			Segment B1	Segment B2	Segment B3
Attribute level part-worth utility (zero-centered dfiferences)	**Degree of autonomy**	Conventional	12.97	14.54	24.63
		Partial. auton.	16.23	15.08	26.60
		Fully auton.	−29.20	−29.61	−51.23
	Vehicle size	Conventional	44.71	−98.08	38.06
		Larger tractors	−47.29	20.18	−41.73
		Smaller tractors	2.58	77.90	3.67
	Price increase	None	81.56	14.93	57.07
		Moderate	−0.56	32.20	28.26
		Strong	−81.00	−47.13	−85.33
	'None'-option		−69.45	−212.25	424.55

Table 8
Socio-demographic composition of segments in Experiment B (n = 645).

		B1	B2	B3	Chi^2	df	p	Cramér's V
		Shares in %						
Sex	Male	52.9	49.8	47.1	0.97	2	0.617	0.039
	Female	47.1	50.2	52.9				
Age (*)	< 40 years	35.3	35.4	18.6	7.85	2	0.020	0.110
	≥ 40 years	64.7	64.6	81.4				
Education (***)	No Abitur	52.5	65.0	74.3	15.49	2	0.000	0.155
	Abitur or higher	47.5	35.0	25.7				
Size of place of residence	< 5,000 inhab.	13.3	12.8	17.1	2.04	4	0.719	0.057
	5,000–100,000 inhab.	52.2	55.2	55.7				
	> 100,000 inhab.	34.5	32.0	27.1				
Experience in agric. or related sector	Yes	7.2	9.1	8.6	0.70	2	0.705	0.033
	No	92.8	90.9	91.4				
Farmers in personal network	Yes, we discuss farming-related topics	18.7	23.9	11.4	6.98	4	0.137	0.104
	Yes, but we do not discuss farming-related topics	16.5	13.1	15.7				
	No	64.7	63.0	72.9				

Pearson Chi^2-Test of Independence: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9
Attitudinal profiles of segments in Experiment B (n = 645).

	Seg-ment	Median	Likert-type scale				
			Fully disagree	**Rather disagree**	**Unde-cided**	**Rather agree**	**Fully agree**
			Shares in %				
Digital farming technologies alienate the farmer from his/her land or animals. (***)	B1[a]	undecided	3.2	23.7	41.4	23.4	8.3
	B2[b]	undecided	7.7	37.7	29.6	21.2	3.7
	B3[a, b]	undecided	2.9	21.4	54.3	12.9	8.6
Family farming structures seem valuable and should be preserved. (*)	B1[a, b]	rather agree	1.1	1.4	8.6	42.4	46.4
	B2[a]	fully agree	0.3	1.3	6.1	38.7	53.5
	B3[b]	rather agree	1.4	1.4	22.9	30.0	44.3
I am scared of modern agricultural machines. (**)	B1[a]	rather disagree	25.9	38.5	20.5	11.5	3.6
	B2[a]	rather disagree	25.3	42.4	17.8	11.1	3.4
	B3[b]	undecided	11.4	30.0	40.0	12.9	5.7
Farmers should have more leisure time. (***)	B1[a]	rather agree	0.4	3.6	34.9	45.3	15.8
	B2[b]	rather agree	0.0	1.3	20.5	52.5	25.6
	B3[a]	rather agree	1.4	0.0	38.6	50.0	10.0
I consider the preservation of the environment for future generations very important. (**)	B1[a, b]	fully agree	1.1	2.9	8.6	33.1	54.3
	B2[a]	fully agree	0.0	0.0	5.7	33.7	60.6
	B3[b]	rather agree	0.0	0.0	15.7	37.1	47.1

Kruskal-Wallis H test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Dunn-Bonferroni post-hoc Test:[a, b] segments with the same superscripts do not differ significantly from each other.

group of participants (10.6 %) that give highest importance to the price attribute (47.5 %) but, unlike Segment B1, barely differentiates between the two technical attributes (25.9 % and 26.6 %, respectively).

The attribute level part-worth utilities (Table 7) allow for further characterization between the segments but are not as conclusive as in Experiment A. The attribute 'degree of autonomy' is considered least important by all segments, and all segments show the same distribution of preferences. They reject fully autonomous tractors and derive comparable levels of positive utility from both conventional and partially autonomous tractors. The attribute 'vehicle size', on the other hand, sees more differentiation. Segments B1 and B3 share the same utility pattern, as members of both segments prefer conventional vehicle sizes and reject larger-than-conventional vehicles. For both segments, smaller-than-conventional vehicles generate low levels of positive utility. The same can be said for 'price increase', although Segment B1 sees a greater drop in utility from no to moderate price increases than Segment

Table 10
SIA-score profiles of segments in Experiment B (n = 645).

	Seg-ment	Median	SIA-score						
			−3	−2	−1	0	1	2	3
			Shares in %						
'small swarm robots' (**)	B1[a, b]	0	0.7	4.7	12.9	41.4	23.4	11.9	5.0
	B2[a]	0	0.7	2.7	9.8	40.1	22.6	13.5	10.8
	B3[b]	0	1.4	4.3	10.0	62.9	12.9	8.6	0.0
'large autonomous tractor' (***)	B1[a]	0	3.2	7.2	18.0	37.8	19.8	10.1	4.0
	B2[b]	0	3.0	3.0	9.8	34.3	22.6	15.8	11.4
	B3[a]	0	2.9	10.0	8.6	55.7	15.7	4.3	2.9

Kruskal-Wallis H test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a, b] segments with the same superscripts do not differ significantly from each other.

Table 11
Summary of hypotheses evaluation based on Experiments A and B.

Hypothesis	Statement	Conclusion
H1	Individuals who agree that digital farming technologies lead to alienation of the farmer from his/her land or animals prefer conventional technologies	no conclusion possible
H2	Individuals who agree that family farming structures seem valuable and should be preserved prefer conventional technologies.	hypothesis rejected
H3a	Individuals who indicate to be scared of modern agricultural machines prefer conventional tractors over large autonomous tractors in Experiment A.	hypothesis rejected
H3b	Individuals who indicate to be scared of modern agricultural machines prefer small tractors over large or conventional tractors sizes in Experiment B.	hypothesis rejected
H4	Individuals who agree that farmers should have more leisure time prefer fully autonomous tractors over partially autonomous tractors and both types over human-driven tractors in Experiment B.	hypothesis rejected
H5a	Individuals who agree that they consider preservation of the environment for future generations very important prefer hoeing over spot-spraying and both digital technologies over conventional weed control in Experiment A.	hypothesis supported
H5b	Individuals who agree that they consider preservation of the environment for future generations very important prefer small tractors in Experiment B.	hypothesis supported
H6	Individuals with a positive SIA-score on the image of small swarm robots prefer digital and autonomous technologies.	hypothesis rejected
H7	Individuals with a positive SIA-score on the image of a large autonomous tractor prefer digital and autonomous technologies.	hypothesis rejected

B3. The two segments differ markedly on the 'none'-option, which provides low negative utility to Segment B1 but high positive utility to Segment B3. A high positive utility for the 'none'-option may indicate that participants did not consider any of the presented choice cards, i.e., technology-price combinations, attractive enough to choose or that they

Table A2
Kruskal-Wallis H test results for Likert-type statements and spontaneous image associations in Experiment A (two-sided test).

Item	H	df	p	compared segments	Bonferroni-corrected significance
Digital farming technologies alienate the farmer from his/her land or animals.	1,155	2	0.561	A1-A2	
				A1-A3	
				A2-A3	
Family farming structures seem valuable and should be preserved.	22,524	2	0.000	A1-A2	0.000
				A1-A3	0.012
				A2-A3	0.023
I am scared of modern agricultural machines.	6,428	2	0.040	A1-A2	0.040
				A1-A3	0.521
				A2-A3	0.332
Farmers should have more leisure time.	10,359	2	0.006	A1-A2	0.013
				A1-A3	1.000
				A2-A3	0.005
I consider the preservation of the environment for future generations very important.	25,188	2	0.000	A1-A2	0.000
				A1-A3	0.001
				A2-A3	0.064
SIA-score 'small swarm robots'	15,329	2	0.000	A1-A2	0.000
				A1-A3	0.870
				A2-A3	0.004
SIA-score 'large autonomous tractor'	10,586	2	0.005	A1-A2	0.050
				A1-A3	0.638
				A2-A3	0.004

Table A1
Distribution and Pearson Chi^2 Test of Independence for socio-demographic variables between the total sample, from which the experimental samples were drawn, and the population (German residents older than 18 years with access to the internet).

Size		Total sample	Population*	Chi^2	df	p
		n = 2,012	N = 51.6 million			
		shares in %				
Sex	Female	50.2	48.4	2.753	1	0.097
	Male	49.8	51.6			
Age	< 40 years	35.0	37.0	3.361	1	0.067
	≥ 40 years	65.0	63.1			
Level of education	No university entrance qualification (Abitur)	63.0	63.2	0.023	1	0.878
	University entrance qualification (Abitur) or higher	37.0	36.9			
Size of place of residence	< 5,000 inhabitants	14.1	14.0	0.340	2	0.844
	5,000–100,000 inhabitants	53.4	53.0			
	> 100,000 inhabitants	32.5	33.1			

* based on the report "Markt-Media-Analyse b4p 2017 III Märkte + Menschen".

Table A3
Kruskal-Wallis H test results for Likert-type statements and spontaneous image associations in Experiment B (two-sided test).

Item	H	df	p	compared segments	Bonferroni-corrected significance
Digital farming technologies alienate the farmer from his/her land or animals.	18,171	2	0.000	B1-B2	0.000
				B1-B3	1.000
				B2-B3	0.112
Family farming structures seem valuable and should be preserved.	7,394	2	0.025	B1-B2	0.191
				B1-B3	0.598
				B2-B3	0.042
I am scared of modern agricultural machines.	13,497	2	0.001	B1-B2	1.000
				B1-B3	0.003
				B2-B3	0.001
Farmers should have more leisure time.	26,616	2	0.000	B1-B2	0.000
				B1-B3	1.000
				B2-B3	0.001
I consider the preservation of the environment for future generations very important.	7,848	2	0.020	B1-B2	0.108
				B1-B3	0.837
				B2-B3	0.048
SIA-score 'small swarm robots'	14,304	2	0.001	B1-B2	0.050
				B1-B3	0.136
				B2-B3	0.001
SIA-score 'large autonomous tractor'	29,428	2	0.000	B1-B2	0.000
				B1-B3	1.000
				B2-B3	0.000

did not care enough about the topic of the experiment to deal with the choices. Segment B2, on the other hand, prioritizes differently on 'vehicle size' and 'price increase' attributes. Its members reject conventional-sized tractors and prefer smaller-than-conventional vehicles. Larger-than-conventional vehicles rank between the other two options for this segment, which considered 'vehicle size' the most important attribute. This segment also derives higher utility from moderate price increases than from no price increases at all, although rejecting strong price increases. The utility derived from the 'none'-option is substantially more negative than for Segment B1.

3.2.2. Segment description

Investigation of socio-demographic differences between the segments only yields significant results for the level of education and, to a lesser extent, age (Table 8). Members of Segments B1 and B2 are below 40 years of age more often than members of Segment B3, who are comparatively older. However, Segment B1 stands out due to its high rate of participants who have achieved higher levels of education. Both Segments B2 and B3 rank lower in this regard.

The attitudinal profile (Table 9) allows for more detailed distinction between the segments. The detailed test results are reported in the appendix (Table A3). The statement 'Digital farming technologies alienate the farmer from his/her land or animal' now produces significantly different rates of agreement between the segments. Segment B1 shows comparable rates of agreement as Segment B2 but also significantly higher indecisiveness on the statements of farmer alienation through digitalization and increased leisure time for farmers. Segment B2 shows significantly stronger disagreement with the statements about farmer alienation through digitalization and fear of modern agricultural machines than one or both of the other two segments, respectively. On the other hand, this group of participants agrees more strongly with increased leisure time for farmers than either of the other segments. Segment B3 is undecided significantly more often than one or both other segments on the statements about preservation of family farms, fear of modern agricultural machines, and preservation of the environment.

The SIA-scores (Table 10) support the impression of Segment B3 being undecided most often and Segment B2 having the most positive attitude towards agricultural technology. The former effect is particularly visible for the image of small swarm robots. Conversely, the comparatively more positive attitude of Segment B2 is more pronounced for the image of the large autonomous tractor. The distribution of SIA-scores for Segment B1 is positively skewed for the small swarm robots and evenly distributed for the large autonomous tractor.

3.3. Inter-experiment comparison

Characterizing the segments from multiple perspectives (socio-demographic composition, attitudes, and spontaneous image associations) allows for distinction between the segments within each experiment while also providing the opportunity to compare segments between experiments. Overall, the segments showing the most active participation in the experiment, as demonstrated by their rare choice of the 'none'-option, comprise almost half of the participants in each experiment (47.2 % in Experiment A, 47.0 % Experiment B). Conversely, those least interested in the topic, i.e., showing a high positive coefficient for the 'none'-option, make up only small groups (12.7 % in Experiment A, 10.6 % in Experiment B).

Segments A3 and B2 are characterized by strongly negative part-worth utility for the 'none'-option and positive part-worth utility for moderate price increases, suggesting interest in the technologies treated in the experiments (cf. Tables 3 and 7). Both show an above-average

Table A4
Distribution and Pearson Chi^2 Test of Independence for socio-demographic variables between the total sample, from which the experimental samples were drawn, and the population (German residents older than 18 years with access to the internet).

		Segments		Chi^2	df	p	Cramér's V
		A3	B2				
		Share in %					
Sex	Male	49.2	49.8	0.02	1	0.887	0.005
	Female	50.8	50.2				
Age	< 40 years	38.5	35.4	1.92	1	0.165	0.053
	≥ 40 years	61.5	64.4				
Level of education	No Abitur	34.3	35.0	0.15	1	0.697	0.015
	Abitur or higher	65.7	65.0				
Size of place of residence	< 5,000 inhab.	15.9	12.8	2.67	2	0.264	0.062
	5,000–100,000 inhab.	56.0	55.2				
	> 100,000 inhab.	28.2	32.0				
Experience in agric. or related sector	Yes	11.7	9.1	3.22	1	0.073	0.068
	No	88.3	90.9				
Farmers in personal network	Yes, we discuss farming-related topics	23.2	23.9	3.59	2	0.166	0.072
	Yes, but we do not discuss farming-related topics	15.2	13.1				
	No	61.5	63.0				

Pearson Chi^2-Test of Independence: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5
Distribution and Pearson Chi^2 Test of Independence for socio-demographic variables between the total sample, from which the experimental samples were drawn, and the population (German residents older than 18 years with access to the internet).

		Segments		Chi^2	df	p	Cramér's V
		A1	B1				
		Share in %					
Sex	Male	47.3	52.9	1.71	1	0.190	0.055
	Female	52.7	47.1				
Age	< 40 years	38.2	35.3	0.51	1	0.475	0.030
	≥ 40 years	61.8	64.7				
Level of education	No Abitur	44.2	47.5	0.62	1	0.431	0.033
	Abitur or higher	55.8	52.5				
Size of place of residence	< 5,000 inhab.	14.5	13.3	0.65	2	0.721	0.034
	5,000–100,000 inhab.	48.8	52.2				
	> 100,000 inhab.	36.7	34.5				
Experience in agric. or related sector	Yes	3.9	7.2	2.94	1	0.086	0.072
	No	96.1	92.8				
Farmers in personal network (**)	Yes, we discuss farming-related topics	15.5	18.7	6.78	2	0.034	0.110
	Yes, but we do not discuss farming-related topics	10.2	16.5				
	No	74.2	64.7				

Pearson Chi^2-Test of Independence: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6
Distribution and Pearson Chi^2 Test of Independence for socio-demographic variables between the total sample, from which the experimental samples were drawn, and the population (German residents older than 18 years with access to the internet).

		Segments		Chi^2	df	p	Cramér's V
		A2	B3				
		Share in %					
Sex	Male	49.4	47.1	0.08	1	0.781	0.022
	Female	50.6	52.9				
Age	<40 years	26.5	18.6	1.36	1	0.244	0.094
	≥40 years	73.5	81.4				
Level of education	No Abitur	25.3	25.7	0.00	1	0.953	0.005
	Abitur or higher	74.7	74.3				
Size of place of residence	<5,000 inhab.	15.7	17.1	2.78	2	0.249	0.135
	5,000–100,000 inhab.	44.6	55.7				
	>100,000 inhab.	39.8	27.1				
Experience in agric. or related sector	Yes	2.4	8.6	2.91	1	0.088	0.138
	No	97.6	91.4				
Farmers in personal network	Yes, we discuss farming-related topics	7.2	11.4	5.05	1	0.080	0.182
	Yes, but we do not discuss farming-related topics	6.0	15.7				
	No	86.7	72.9				

Pearson Chi^2-Test of Independence: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

connection to the agricultural sector and make choices that align with presently or soon-to-be market-available technologies. The two segments do not differ significantly in their socio-demographic variables (Table A4).

Comparing the two segments characterized by high levels of education, A1 and B1, opposing attitudes emerge. Segment A1 shows strong support for herbicide-reducing methods of weed control and indicates a certain price flexibility. To the contrary, Segment B1 is highly sensitive to price changes and prefers conventional or only slightly digitalized technology. Segment A1 also presents a much sharper attitudinal profile, indicating strong opinions on multiple statements. While Segment B1′s response pattern follows the same tendency as that of Segment A1, it comprises high rates of indecisiveness. These two segments differ significantly only in the percentage of individuals reporting to have farmers in their personal network (Table A5), which is lower for Segment A1.

The final two segments, A2 and B3, both claim the smallest share of participants in their respective experiment and are strongly price sensitive but also show a high positive utility for the 'none'-option. They frequently chose technology characteristics corresponding to the status-quo, which suggests indifference to the survey subject when combined with the attitudinal and SIA-score profiles. The demographic composition points to low rates of higher education and indicatively or significantly higher rates of over-40-year-olds as well as lower personal connections to the farming sector, which may correlate with a lower overall understanding of the presented digital technologies and their consequences. These last two segments do not differ significantly in their socio-demographic variables (Table A6).

3.4. Evaluation of hypotheses

The proposed hypotheses were evaluated in a qualitative manner based on the identified segments' part-worth utilities within the relevant attributes as well as their responses to the Likert-type statements and their SIA-scores. Of nine hypotheses, six were rejected while one could not be evaluated conclusively (see Table 11). The results of the present evaluation support two of the hypotheses. Based on these results only limited conclusions on the effect of preferences for conventional compared to digital and/or autonomous technologies can be drawn.

The first four hypotheses (H1, H2, H3a, H3b) may be considered emotion-focused. However, their evaluation suggests that consumers' responses to the respective statements are not a good indicator of their opinion on autonomous technology. It cannot be evaluated conclusively that individuals' fear of farmer alienation from his/her soil or animals influences the preference for conventional technologies (H1). Some evidence from Experiment B supports this hypothesis as the segment preferring non-conventional tractor sizes disagrees with this statement more often than the segment preferring conventional tractor-sizes. However, the feebleness of this argument is underscored by the lack of any significant differences between the segments in Experiment A on this statement. Conversely, the hypothesis that digital and autonomous technologies contradict the concept of family farming (H2) can be rejected as there is some evidence from both experiments that those individuals who agree with the preservation of family farms more strongly actually prefer small swarm robots, spot-spraying and hoeing, or smaller-than-conventional tractors. Despite this preference for small technologies, the set of hypotheses investigating the link between fear of modern agricultural machines and rejection of autonomous vehicles (H3a, H3b) can also be rejected. In both experiments, most participants disagree with this statement although one segment each is indifferent significantly more often than the other two. However, this pattern does not align with preferences for conventional tractors over large autonomous tractors or small swarm robots nor with preferences for vehicle size. These emotionally driven attitudes can thus not be utilized to predict consumers' opinion of crop robots.

A second set of hypotheses covers more rational aspects (H4, H5a, H5b). The importance attributed to more leisure time for farmers shows no relationship to the evaluation of vehicle autonomy in Experiment B (H4) so that this hypothesis, too, must be rejected. Consumers' environmental concerns, on the other hand, do appear to influence the preferences for weed management technologies (H5a) and vehicle size (H5b). In Experiment A, the segment agreeing with the statement on preservation of the environment significantly more often is also the segment indicating the highest importance for the attribute 'method of weed control as well as preferring hoeing to spot-spraying and both technologies to conventional spraying. In Experiment B, the evidence is somewhat less pronounced. Nonetheless, one segment's agreement with environmental preservation stands out and corresponds to a comparatively strong preference for smaller tractors, both relative to the utilities derived from the other attribute levels and relative to the other segments' utility levels for smaller-than-conventional tractors. Conclusively, consumers' attitudes toward environmental preservation for future generations seem to relate positively to their opinion on digital and autonomous farming technology.

The final two hypotheses (H6, H7) aimed to investigate a relationship between spontaneous image associations and cognitively more active weighting of technology attributes and consumer prices. However, for neither small swarm robots (H6) nor large autonomous tractors (H7) was there any evidence to support the idea that consumers' spontaneous reactions to images of crop robots corresponds to their more reasoned evaluation of the technology.

4. Discussion and implications

4.1. Summary and context

The present investigation studied the German public's preferences regarding the use of crop robots to respond to farmers' concerns about societal reactions to this novel technology. The two subsamples could each be grouped into three distinct segments comparable between the two experiments. Although a small group of participants in the experiments was rather indifferent towards the use of autonomous technologies and crop robots, as indicated by the selection of the 'none'-option, the majority of participants conversely had an opinion to share. The investigated hypotheses demonstrate that participants' views on preservation of family farming, intimidating agricultural machinery, or reduced farmer workload do not influence their evaluation of digital and/or autonomous equipment in crop production. The relationship between stated technology preferences and opinion on the questions of farmer alienation through digitalization was inconclusive. Additionally, although the spontaneous image associations were largely positive, they did not correspond clearly to stated technology preferences, which is in line with Römer et al.'s (2019) findings of differences between implicitly and explicitly stated attitudes. As such, no explicit response can be made to farmers' concerns about negative societal reactions to purchasing crop robots (Rübcke von Veltheim et al., 2021; Spykman et al., 2021a). However, there is evidence that survey participants who value environmental preservation also prefer digital or autonomous solutions in crop production. Additionally, there is consensus between all identified segments in the respective experiments that spot-spraying represents an improvement from conventional spraying and that partially or fully autonomous tractors are preferable to conventional tractors.

Public acceptance of crop robots is only just emerging as a subject in agricultural research. Dutch agri-food experts expect the environmental benefits of crop robots to convince Dutch consumers, who are presumed to be rather conservative-nostalgic regarding food production, yet also state these environmental benefits must not be taken for granted (van der Burg et al., 2022). The general idea of environmental benefits being a driver of crop robot acceptance, however, is also reflected in the present results. On the other hand, the use of robots could also replace the craftsmanship of farmers (van der Burg et al., 2022), which may be resented by more traditionalist consumers. This aspect ties into the idea of 'naturalness' of food production, which is an important aspect in public acceptance of food technologies. Due to the fact that modern-day consumers are far removed from the reality of food production (Salamon et al., 2014; Zander et al., 2013), they tend to apply a 'natural-is-better' heuristic approach. Consumers believe the food industry to be capable of producing safe food, yet do not trust the industry to value consumer health over company profit (Siegrist & Hartmann, 2020). The idea of 'natural-is-better' appears to be reflected in the present DCE analysis result of preference for herbicide-reduced methods of plant protection and also corresponds to the rejection of agro-chemicals as 'unnatural' (Salamon et al., 2014; Zander et al., 2013) and risky (Lehberger & Becker, 2021). Yet the difference of the technologies (e.g., gene editing, nanotechnology) reviewed by Siegrist and Hartmann (2020) relative to crop robots is that they influence the consumer product directly rather than the production processes.

It therefore appears more sensible to compare the technology-product-consumer relationship of crop robots with that found in dairy production, which has already adopted a broad range of automation technologies. The present data set suggests that automation in dairy production is partially viewed more critically than in crop production (Pfeiffer et al., 2021; Spykman et al., 2021a). Consumer attitudes towards automated milking systems tend to be predominantly positive, but some consumer groups also voice concerns about decreases in animal welfare, decreases in milk quality, and the risk of humans being replaced by machines (Henchion et al., 2022). While animal welfare has no direct equivalent in crop production, food quality and job loss could also become issues in arable farming (cf. Marinoudi et al., 2019 for employment effects of crop robots). Neither of these two issues were investigated in the present analysis and should therefore be considered for further research. The present results do not necessarily reflect the idea of caution toward modernity (cf. Boogaard et al., 2011), but the herein conducted LCA reveals stark differences between different societal segments, supporting Boogaard et al.'s (2011) conclusion that different societal groups hold different core values that influence their attitudes toward modern agricultural technologies. Both the present findings as well as those from literature surveying the dairy sector thus point to the importance of understanding societal motives behind acceptance or rejection of automation technologies in primary food production. The differentiation between societal segments should therefore also be considered in future research on societal acceptance of automation in all agricultural sectors.

4.2. Limitations

The data for this study were collected through an online survey among a consumer panel managed by a professional field service provider. While this decision was motivated by research economics, i.e., reaching a large sample in a time- and cost-efficient manner (cf. Comley & Beaumont, 2011), the sample thus obtained is not random and may be skewed relative to the 'real' German population. Access to the survey was clearly limited to individuals with access to the internet. In addition, members of a panel self-select to join the panel, which may impede representativeness of the population further (Göritz & Moser, 2000; Leiner, 2016), although quality control measures for panel composition do exist (Comley & Beaumont, 2011). The problem of representativeness was further addressed in the present sample through pre-quotation, i.e., the setting of required distributions for four socio-demographic variables to ensure their comparability to the distribution in the German population. While quotation may not yield full representativeness, as internet users may not necessarily be representative of non-internet users (Göritz & Moser, 2000), the majority of the German population (87 %) in 2018, the year of the survey, frequently used the internet (agof e.V., 2022; DESTATIS, 2020). The representativeness of online panels thus likely improved over the past two decades (cf. Göritz & Moser, 2000), although it should be noted that individuals over the age of 60 years still use the internet much less frequently than younger individuals (agof e.V., 2022). After the sampling process was concluded, the dataset was cleaned from entries with implausible response behavior to control for 'professional' survey respondents (cf. Comley & Beaumont, 2011).

In the present study, although a comparison between segments was attempted, the results need to be interpreted with caution. Both attribute importance and attribute-level part-worth utility values are measured on dimensionless scales that are only comparable within one experiment. Consequently, absolute utility levels must not be compared between experiments, thus limiting comparability even between segments of similar socio-economic characteristics. A more clear-cut benchmark for comparison appears necessary. Additionally, it is only possible to conclude relative levels of preference or rejection based on the attributes and attribute-levels included in each experiment, i.e., no statements regarding preferences outside the experimental setting can be made. This points to a limitation of the methodological approach as the relative preference of the herein assessed technologies cannot be compared to technologies not considered in the DCE. The DCE's prescriptive frame stands in contrast to the qualitative evaluation of the hypotheses, which should be considered as indicative, although being consistent with Pfeiffer et al. (2021)'s analyses. The presented findings should be tested using qualitative methods that allow for free responses from participants, e.g., consumer focus group discussions or stakeholder interviews. These could draw on the present findings of level of education and personal connections to the agricultural sector significantly influencing consumer segment membership and investigate demographic and attitudinal relationships in more detail. However, the values of Cramér's V obtained for these relationships remained below the threshold for meaningful effect sizes, so that additional research is indeed necessary to corroborate the present findings. Consumer acceptance of crop robots in Germany could, e.g., be investigated under consideration of different attributes or a larger number of segments. The latter could improve differentiation but may also complicate interpretation and comparability with other economic settings.

Indeed, the present findings cannot be easily transferred to other countries and economic settings as consumer attitudes towards technologies in food production vary internationally (Siegrist & Hartmann, 2020). While the present results indicate a rather positive attitude of German consumers towards crop robots, a European survey suggests that the German population actually shows a negative tendency towards robots in general relative to other members of the EU. However, the survey also suggests that agriculture specifically is not seen as a priority use case for robots by most of the European population (Eurobarometer, 2014), so that there is little information how findings from Germany may transfer to other countries. Additionally, much progress in the crop robot market has occurred since the publication of the report. It thus remains to be answered whether consumer attitudes towards crop robots in other countries follow the pattern identified a decade before the present study or whether technological developments since then have influenced public opinion. The presented results thus provide a substantial starting point to further advance the not yet well-developed body of literature on public perception of digital and autonomous agricultural technology.

4.3. *Opportunities for further research*

When comparing consumer attitudes towards crop robots internationally, non-industrialized, i.e., emerging and developing economies, should actively be included in this growing body of literature on public acceptance of crop robots as well as agricultural digitalization at large. It appears that digitalization, although generally viewed as advantageous for the agricultural sector, is met with the similar apprehensions in both industrialized and non-industrialized nations: high investment costs, poor network coverage, low levels of ICT knowledge among farmers – all relevant for a growing digital divide between farms – and yet uncertain effects on the rural job market (Daum et al., 2022; Hackfort, 2021). However, the magnitude of these and further issues will vary per country and thus also influence societal acceptance differently; for example, nations with a high share of the population relying on agriculture as a source of income, as is the case in non-industrialized nations, may suffer more from autonomization replacing manual labor than a nation like Germany, where manual labor is scarce and crop robots are needed to fill the gaps. In addition to differences in economic weight of the agricultural sector between industrialized and non-industrialized nations, the frequently low levels of basic mechanization and the global benefit of input-efficient yield increases through precision technologies in developing nations (Mizik, 2022) also need to be considered.

Education appears to be the common thread in acceptance of digital technologies in agriculture among both farmers and the non-farmer society. While the present study found the segments with the lowest interest in autonomous agricultural equipment to also have the lowest rates of higher education. Similarly, farmers without higher education have been found to be less ready to accept digital (Schulze Schwering et al., 2022) and autonomous (Rübcke von Veltheim & Heise, 2021) technologies. Even for more general precision agriculture technologies, education, in addition to farm size, is a dominant influence (Mizik, 2022). The question remains whether this divide is to be overcome by increased rates of higher education or rather a change in the content of vocational training for farmers. Given the indication that level of education and digital farming technology acceptance are positively related both among farmers and non-farmers, a gap in education on digital technologies in general, not just with respect to farming, is possible. The role of education on digitalization acceptance and adoption and thus the realization of its expected benefits in the farming sector warrants more thorough investigation.

The assumed benefits of crop robots indeed need to be analyzed in more detail. While reduced soil compaction and reduced pesticide use are virtually self-evident, depending on the type of crop robot, other environmental impacts may not be so obvious. These include, for example, the CO_2-emissions resulting from the storage of data produced by digital agriculture applications in general (Kayad et al., 2022) as well as the resources required to produce the hardware. Additionally, both diesel- and electrically powered crop robots are currently market-available, influencing both crop robots resource consumption as well as, presumably, in their societal acceptance. Thus, life-cycle assessments and analyses of rebound effects of crop robots should be conducted once sufficient data on their useful life is available to inform all relevant stakeholders about the actual role crop robots may play on the way to more sustainability in agriculture.

4.4. *Outlook and conclusion*

The outcomes of this study may be valuable to stakeholders in policymaking, research, farming, and manufacturing in industrialized nations with conditions comparable to Germany. Whereas the machine sizes of market-available crop robots and publicly presented case studies vary strongly, illustrating that optimal crop robot size is still an open question for manufacturers and farmers (cf. Lowenberg-DeBoer et al., 2020), the public is less interested in this aspect. Although favoring small crop robots (also Pfeiffer et al., 2021), the public is more concerned about the purpose of crop robots, i.e., the reduction of agro-chemicals. In this context, it is remarkable that spot-spraying already signifies a stark improvement from conventional spraying in the opinion of the public, despite the continued use of herbicides. Additionally, the fraction of society most strongly connected to practical agriculture even prefers spot-spraying to purely mechanical weeding. For this reason, research and development activities as well as government funding should focus technologies aiming to reduce the use of herbicides and other agro-chemicals, analogous to Jacquet et al. (2022)'s call for a new pesticide-free research paradigm in agriculture. This is also in line with cautions of rebound effects such as a crop robot-induced increase in agro-chemical usage due to lower costs or more potent formulations as humans are no longer involved in their application (Sparrow & Howard, 2021). Such a reduction of pesticides is in agreement with the largest consumer groups in the present investigation who portray a generally positive attitude towards autonomous crop robots but disregard the technology's degree of autonomy compared to its purpose. Farmers and their representatives should therefore also focus on environmental rather than economic benefits when communicating with the public, and general media communication about digitalization in agriculture should inform the public about the topic's relevance for issues of concern to society.

CRediT authorship contribution statement

Olivia Spykman: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Agnes Emberger-Klein:** Methodology, Formal analysis, Writing – review & editing. **Andreas Gabriel:** Conceptualization, Investigation, Data curation, Writing – review & editing. **Markus Gandorfer:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A

See Tables A1-A6.

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