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# Farmers' perspectives on field crop robots – Evidence from Bavaria, Germany

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ABSTRACT

Farmers' attitudes toward field crop robots in a European setting have hardly been studied despite an increasing availability of the technology. Given the relevance of robots for small-scale agriculture, however, their acceptability in regions dominated by small-scale agriculture such as Bavaria, Germany, is of particular interest. Based on a sample of 174 farmers, an exploratory investigation of factors influencing the preference for large or small field crop robots in general and in specific settings and for mode of operation was carried out. Data were gathered using questionnaires at two events including lectures and field demonstrations and analyzed using bivariate tests. Farm size, farming system (organic/conventional), and occupational structure (part-time/full-time) were relevant attributes influencing the evaluation of advantages and disadvantages of field crop robots. Generally, respondents from larger farms focus more on financial benefits from robots and prefer large autonomous tractors. Conversely, small-scale or organic farmers consider environmental benefits of field crop robots relatively more important and favor small robots. Organic farming also positively correlates with the intent to purchase field crop robots within the next five years. More farmers can generally imagine owning small robots as opposed to an autonomous tractor in ten years, but at the same time view autonomous tractors as more suitable for most specified agronomic tasks. Non-purchase options such as contractor services and machinery sharing represent the preferred modes of robot deployment.

## 1. Introduction

### 1.1. Overview of field crop robots

Robots are built to automate repetitive, dull, strenuous, or hazardous tasks, which may include manual weeding, harvesting, spraying, or tractor driving in an arable farming context. Corresponding to the definition proposed by Lowenberg-DeBoer et al. (2020), the following analysis considers *field crop robots* as ground-borne technologies automating human tasks in field crop production without permanently requiring a human driver or remote operation, although human intervention may occasionally become necessary (cf. levels 3 and 4 in SEA International, 2018). One can differentiate between large and small field crop robots, both of which may work individually or as part of a swarm or fleet. Field crop robots may be driven by a combustion engine powered by fossil or bio-based fuels or by an electric engine powered by solar or grid energy (Fig. 1), but alternative power sources may be developed in the future.

Large robots resemble traditional tractors in that they can be equipped with various implements but do not require a driver (Gaus et al., 2017), although specialized large robots are also being developed. Manufacturers of conventional tractors in the USA and Japan have already produced prototypes of autonomous tractors without a driver's cab. Additionally, manufacturers are experimenting with different forms of power supply to replace diesel as fuel. Some research projects have also modified commercially available conventional diesel-fueled tractors to work autonomously (e.g. Emmi et al., 2014).

Small robots, on the other hand, may be further differentiated into single- and multi-task machines, with the former being specialized mainly for sowing and crop maintenance, although robots built for other specialized tasks also exist (Gaus et al., 2017). All currently available models are electrified and may be charged on- or off-grid. Multi-task, or platform, robots, on the other hand, are available as electrically powered or diesel-fueled machines. They act as carrier frames for standard

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implements and may thus replace small traditional tractors.

While field crop robots are being hailed as enablers of more sustainable intensification (Bongiovanni and Lowenberg-DeBoer, 2004; Lowenberg-DeBoer et al., 2020), this may only be achieved if robotic solutions are accepted by the various relevant stakeholders: farmers, distributors, contractors, society, and policymakers. Little research on the perception of robotic solutions in crop farming has been carried out to date, though, especially when compared to the substantial body of research on robots in dairy production. The dairy sector was introduced to robots in the 1990s when the first automatic, or robotic, milking system (AMS) entered the market. The spread of AMS sparked research interest in its economic efficiency as well as its impacts on animal welfare, milk quality, or barn structure. AMS investment trends differed strongly between Europe and North America, though, which is attributable to differences in typical herd size, availability of support, and supply of cheap farm labor (Jacobs and Siegford, 2012). Following AMS, robots to automate cattle feeding and barn cleaning were introduced to the market. The dairy sector is thus two to three decades ahead of crop farming regarding the level of robotization, which is evident in the amount of literature available (cf. Jacobs and Siegford, 2012).

Compared to the comprehensive evaluation of AMS explaining their regionally different acceptance, the information about field crop robots in this regard is only fragmentary. Expert interviews conducted in California suggest that economic factors may both drive and hinder adoption of robotic solutions (Rial-Lovera, 2018). Farmer interviews in Australia indicate concerns about reliability and cost-efficient data storage, but also expectations of decreased pesticide costs and increased amounts of free time as benefits (Redhead et al., 2015). Additionally, Devitt (2018) argues that cognitive factors such as a lack of trust in robot decision making, reduced feeling of connectedness to one's own farm, and apprehensiveness about a lack of social exchange during farm work may negatively affect farmers' acceptance and thus adoption of field crop robots. Recently, Rübcke von Veltheim et al. (2019) assessed the current state of literature on the acceptance of autonomous field crop robots published in English or German and determined an enormous research deficit, especially outside the USA. Subsequently, they interviewed manufacturers of autonomous equipment who expect that field crop robots will first be implemented in specialty crops and organic farming as the economic case for conventional farming is not yet strong enough. The experts further highlight the importance of field size and distribution, predicting that farms with (few) larger fields will adopt field crop robots sooner than farms with (many) small fields, irrespective of total acreage, due to logistics costs (Rübcke von Veltheim and Heise, 2020). A follow-up survey of German farmers allowed for the identification of three clusters, described as 'convinced adopters', 'open-minded supporters', and 'reserved interested'. The clusters have different expectations of field crop robots and correspondingly indicate varying levels of interest to invest. They did not differ significantly, however, in their occupational structure, farming system, or farm size (Rübcke von Veltheim and Heise, 2021).

On a global level, both machines and fields have been increasing in size in the past decades for cost efficiency reasons. Larger machines allow an individual to complete more work in the same amount of time, thus reducing human labor input but also requiring larger fields to use these machines efficiently. This trend has contributed to the difficult stand of the agricultural sector today (de Witte, 2019). Field crop robots show potential to improve the economy of small-scale agriculture, though, and thus also the environmental impact of agriculture. Since the average EU-28 farm size in 2016 was 16.6 ha, with only 15% of European farms actually meeting or exceeding this area (Eurostat, 2019), the economic and environmental opportunities of field crop robots on small-scale farms are highly topical for a large number of European farmers. In addition to potential economic and environmental benefits of field crop robots, social improvements relating to workload and quality of work may be expected. Development in these areas can be considered underlying drivers of a positive attitude toward field crop robots among farmers.

### 1.2. *Economic, ecological, and social evaluation of field crop robots*

#### 1.2.1. *General publication trends*

With regard to socioeconomic and environmental evaluation, field crop robots are not yet well researched. An analysis of the Scopus database, which contains a sizable number of journals relevant to agriculture, yields that publications on field crop robots focus heavily on technology and programming. Publications concerned with environmental or socioeconomic aspects remain low in number despite an overall increasing interest in the field of field crop robots (Fig. 2).

Only two abstracts indicated a purely economic focus while 14 abstracts showed a dual focus on technology and environment or socioeconomics. However, most document abstracts in the economics category focus on cost of the new technology rather than its socioeconomic impact, while in about half the document abstracts placed in the environmental category, environmental benefits were depicted as a consequence of technological innovation rather than main content. In a similar, yet more comprehensive approach, Lowenberg-DeBoer et al. (2020) searched six databases for research on the economics of automated and autonomous agricultural equipment published after 1990. Despite their larger time period and more economics-focused query, albeit considering not only field crop robots, they were able to obtain only 18 publications eligible for further analysis. Their finding corroborates the conclusion drawn from the present analysis of publication abstracts that the current literature on field crop robotics focuses strongly on technological aspects and presents comparatively little insight into their economics. Summarizing the current state of the literature on field crop robotics with respect to their socioeconomic and environmental consequences thus requires making inferences from empirical knowledge about related technologies.

#### 1.2.2. *Economic effects*

Some authors argue that switching from conventional to autonomous equipment (Shockley et al., 2019) and from whole-field to precision approaches (Bongiovanni and Lowenberg-DeBoer, 2004) is associated with increases in net returns. However, the economics of automated technology over conventional machines depends on multiple factors such as processes concerned and farm size. Small-scale field crop robots appear to be economical substitutes for labor-intensive processes by decoupling them from human and legal limitations on daily working hours (de Witte, 2019; Pedersen et al., 2008). This may prove particularly interesting for organic farming (Sørensen et al., 2005). Yet for rather capital-intensive processes like harvesting, large machines,

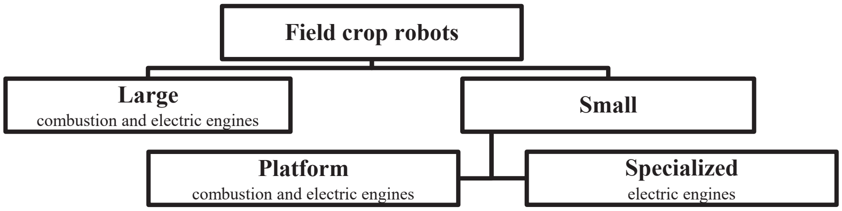

**Fig. 1.** Typology of field crop robots available for arable farming settings including available power sources (source: own compilation)

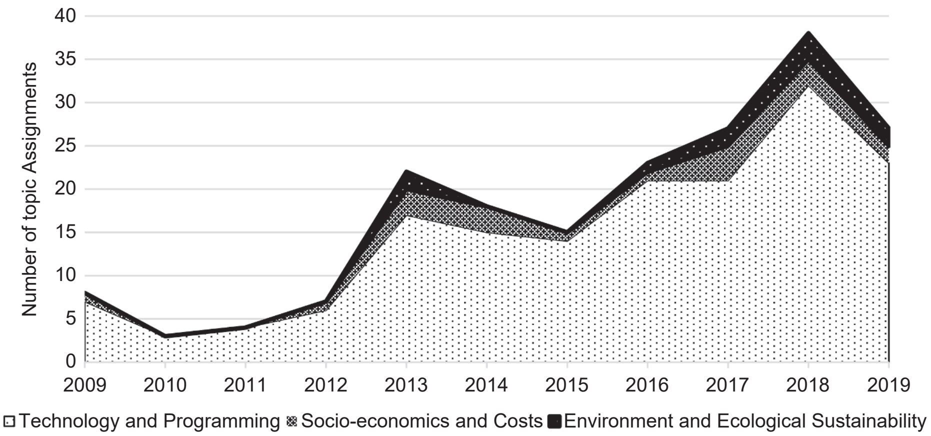

**Fig. 2.** Number of topic assignments per year, includes multiple assignments of individual articles hence cumulative number exceeds total number of documents analyzed (Source: own survey).Two categories of keywords were chosen to select for robotics ('smart robots', 'autonomous robots', 'field robots', and 'agricultural robotics' connected by the Boolean operator OR) and agriculture ('agriculture', connected to first category by the Boolean operator AND). The time period was set to 2009–2019. Only articles, reviews, short-surveys, conference papers, and conference reviews written in English were considered. Their abstracts were analyzed for relevance to field crop robots. The resulting 166 papers were hence categorized as 'socio-economics and costs', 'technology and programming', or 'environment and ecological sustainability', with assignment to more than one category possible.

autonomous or human-operated, retain an economic advantage (de Witte, 2019), although country-specific cost and farming structures will strongly affect individual profitability (Pedersen et al., 2008).

Contrary to the opinion of agricultural technology experts interviewed in Germany (Rübcke von Veltheim and Heise, 2020), small farms with correspondingly smaller fields may generally profit more from automation. A sensitivity analysis on farm size (Shockley et al., 2019) identifies a stark increase in profitability particularly for smaller farms, although limited by the exclusion of used machinery in the model. Similarly, Lowenberg-DeBoer et al. (2019) find that small autonomous tractors may strongly reduce the unit cost of wheat production especially for smaller farms, allowing them to retain previously unprofitable fields, compete on an international level, and reduce their dependence on government subsidies. On the other hand, Lampridi et al. (2019) find that autonomous weeding processes outperform conventional tractors economically only on small rather than large farms, but also only when ignoring labor costs entirely, underlining the multiple factors playing into the economic evaluation of field crop robots. Contrasting the case for robots and small field sizes are the findings of Zhang and Noguchi (2017) whose multi-robot tractor system proved more efficient on longer fields due to the reduced number of headland turns relative to field size. Their study also points to the relevance of multi-robot driving patterns on the field. Further possible economic benefits from the automation of agronomic processes include reduced yield risk, reduced input costs, and costs avoided due to reduced environmental externalities (Gaus et al., 2017; Shockley et al., 2019).

### 1.2.3. *Environmental effects*

Small robots in particular also reduce the negative impact of cultivation processes on soil structure and biota due to their comparatively low weight (Shockley et al., 2019). With the increase in profitability of small, irregularly shaped fields due to autonomous machinery (Lowenberg-DeBoer et al., 2019; Shockley et al., 2012), ecosystem benefits from smaller field sizes may also be expected (e.g. Fahrig et al., 2015). Additionally, solar power is incorporated in the development of field crop robots to further increase their autonomy in the field (Griepentrog et al., 2012), thus reducing the need for fossil fuels. While this tendency is supported by the cost of battery storage continuously decreasing over the past decade and being expected to decrease even further (Cole and Frazier, 2019), the dependence on sufficient hours of sunshine during critical periods may limit this application in some regions.

### 1.2.4. *Social effects*

Health benefits from field crop robots for farmers and farm employees specifically due to the replacement of repetitive manual tasks like weeding are also conceivable. Certain crops, particularly in organic cultivation, require extensive amounts of hand weeding, which increases production costs (Sørensen et al., 2005) and puts physical strain on workers. Prevalent health issues in agriculture may also be associated with stress (Reissig, 2017), agrochemical exposure, or accidents with large machinery. Although conclusive studies on health benefits from the implementation of field crop robotics are lacking, the related time savings (Sørensen et al., 2005) may reduce workload and increase leisure time on family farms (Redhead et al., 2015; Strauss et al., 2014), thus counteracting stress-related illnesses. However, results from an Austrian survey also indicate that farmers operating farms with higher levels of automation face more difficulty finding a vacation replacement (Strauss et al., 2014), possibly generating a new source of stress. The available research on the relationship between robotics and farmer health thus remains inconclusive.

Field crop robots are further expected to make a social impact on the labor market. The European agricultural sector employs a high percentage of seasonal (migrant) workers (Williams and Horodnic, 2018), particularly in specialty crop production. This low-skilled labor especially could be replaced by field crop robots (Marinoudi et al., 2019), although development is also taking place in the area of robot assistants to farmhands (e.g. Baxter et al., 2018). Taking a closer look at Germany specifically, the supply of officially registered seasonal workers already lagged behind demand more than a decade ago (Holst et al., 2008). While more recent information is not available, the decreasing number of farmhands positions field crop robotics as a potential solution to the shortage rather than as a replacement of low-skilled labor. Indeed, the discussion about immigration restrictions due to the Covid-19 pandemic has highlighted the dependence of German agriculture on seasonal migrant workers. High-skilled labor, on the other hand, may be complemented by robotics, thus possibly creating a job polarization phenomenon (Marinoudi et al., 2019). These considerations are underlined by Rotz et al.'s (2019) findings from workshops with scholars and interviews with farmers and other agri-food actors in Canada. Their survey yields that automation technologies may replace unskilled labor to save on wage and transaction costs, e.g. for contracting seasonal migrant workers, but may also allow replacing skilled labor with unskilled labor, as exemplified by automatic steering systems making expensive tractor-driving skills redundant. On the other hand, their interviewees also voiced the need for robot software and sensor experts, underlining the demand for more high-skilled labor due to digitalization in agriculture (Rotz et al., 2019). An example of this may be seen in the development of farming-as-a-service models by manufacturers autonomous technology (e.g. Small Robot Company, 2020). Operation of the robot by a skilled employee eliminates the need for farmer training and allows market introduction before reliability can be fully guaranteed. Clear statements on the social effects of increased digitalization in agriculture cannot yet be made, but certain indications exist for both positive and negative contributions.

### 1.3. Study aim

The review of previous publications has indicated a clear lack of scientific literature on farmers' attitudes toward field crop robots and their potential economic and environmental effects, justifying an investigation into the perception of field crop robots in a small-scale agricultural region to identify relevant leverage points for or potential obstacles to their dissemination. The present research focus lies on the following questions: (1) What are the size and thus function preferences for robots? (2) How do these preferences change in the context of specific agronomic tasks? (3) Do farmers prefer purchasing or renting as operation mode for robots?

In addition to descriptive results, correlations with relevant demographic and structural factors of influence are presented. These links between variables are discussed in the context of existing literature on the adoption of digital farming and precision agriculture as the most closely related areas of research, allowing for further differentiation of the farmer population as future users of field crop robots. The results thus add to the currently sparse body of literature on the dissemination of field crop robots and may prove useful to policymakers, manufacturers as well as equipment dealers and contractors in other small-scale agricultural regions. Fellow researchers may also benefit from the findings to generate hypotheses for replication and confirmatory studies.

## 2. Materials and method

### 2.1. Data collection

A survey was conducted among participants of two field demonstrations of automatic and robotic hoeing technology in 2019 in northern and western Bavaria, Germany. The events comprised both lectures and practical demonstrations, thus possibly attracting a comparatively more open-minded audience, which may result in bias in favor of the queried technologies.

The two-page questionnaire queried the level of usage of different digital agricultural technologies, on potential advantages and problems relating to field crop robots, on likelihood of field crop robot ownership and preferred robot size for certain tasks, and on possible types of ownership and usage. Most groups of questions allowed for 5-point Likert-type answers and generated ordinal data. Depending on the type of question, the levels 1 through 5 were described as 'very unlikely' through 'very likely' (likelihood of field crop robot ownership in ten years), 'very important' through 'not important at all' (perceived advantages of field crop robots), and 'very problematic' through 'not problematic at all' (perceived problems of field crop robots), respectively. Demographic and farm structural information was recorded on varying scales depending on the question. The current level of usage of digital agricultural technologies and preferred type of field crop robot for certain agronomic tasks were measured using a 5- and 4-point nominal response scheme, respectively. The five response options for digital agricultural technology use were 'purchased and in use', 'purchased, but not used', 'purchase planned within the next year', 'purchase planned within the next five years', and 'no purchase planned'. The four response options on task-related robot preference were 'small robots', 'large autonomous tractors', 'both sizes', and 'neither size'.

A total of 186 questionnaires could be collected at the events, but twelve (6.5 %) had to be excluded due to implausible response patterns. Since the remaining 174 datasets (93.5 %) all contained missing data on one or more questions, percentages reported hereafter always refer to the valid responses for the particular combination of variables.

### 2.2. Data analysis

Before testing variables against each other, several modifications were made to the raw data. The continuous variable 'farm size' was generated by adding up the hectare sizes participants entered for each production branch (cash crops, feed crops, grassland, or other). 'Farm size' was then compared to the Bavarian average of 35.3 ha (StMELF, 2018) to create the dichotomous variable 'larger than Bavarian average'. The response options of multinomial questions were combined where appropriate to meet conditions for Chi$^2$-testing. In particular, the questions querying the current level of use of automatic steering systems and intent to invest in crop robots were collapsed to dichotomous variables (i.e. using/not using and planning to invest/not planning to invest).

The literature review has shown that research on factors influencing the adoption of field crop robots is limited. However, as Lowenberg-DeBoer et al. (2019) indicate, field crop robots may be highly relevant to small farms, warranting an investigation of the influence of the variable 'larger than Bavarian average' in the present dataset. In addition to comparatively small farm sizes (StMELF, 2018), Bavarian agriculture is also characterized by part-time farming on every second farm (LfStatD, 2014a). For this reason, the variable 'part-time farming' was investigated. Additionally, market-available digital farming technologies such as automatic steering systems, automatic section control, and implement guidance systems represent a first step into the automation of field work (Thomasson et al., 2019) and may be understood as gateway technologies toward robotics in crop production. Therefore, the possible influence of 'use of automatic steering system' as the most advanced automation technology on the attitude toward field crop robots was investigated. Given further the relevance of automated weeding for organic farming, 'organic farming' was chosen as a final possible influence. The independent variables were thus 'larger than Bavarian average', 'use of automatic steering system', 'organic farming', and 'part-time farming', whose influence on the 'intent to invest in field crop robots' was tested. For questions thereafter, 'intent to invest in field crop robots' was included as a fifth independent variable.

Using these five independent variables, correlations with perceived advantages and disadvantages of field crop robots were tested in order to compare the results to the literature (Devitt, 2018; Redhead et al., 2015; Rial-Lovera, 2018; Rübcke von Veltheim and Heise, 2021, 2020). Given the diverse paths of development of robot size and function described in the introduction, the influence of the identified factors on preference of robot type in general and itemized according to specific agronomic tasks was also tested. Finally, the preferences for mode of operation were studied to understand how 'as a service'-options offered by some manufacturers rank compared to traditional purchase or renting options.

The data were analyzed using IBM ® SPSS ® Statistics Version 26. Nominal-nominal variables were analyzed using Pearson's Chi$^2$-Test of Independence. This test compares the observed number of cell counts with the expected number of cell counts for each combination of the two variables analyzed and becomes significant when the observed distribution of the variables diverges from their expected distribution. The data were recoded as explained above in order to achieve expected cell counts to be at least one in as many cases as possible. Pearson's Chi$^2$-test was then applied to all 2x2-tableaus and those 2x4-tableaus that met the expected cell count-conditions of all expected values being greater than one and at least 80 % of cells having expected values of at least five (Weaver, 2017). For 2x4-tableaus that did not meet these conditions, Monte-Carlo two-sided p-values were calculated using default settings. Thus, the results report the asymptotic two-way significance in most cases and the approximatively exact two-way significance Chi$^2$-value for results of the Monte-Carlo simulation. The discussion is limited to significant correlations with effect sizes of Cramér's V/Phi $\geq 0.2$, as lower values indicate negligible associations between the variables. Since the statistical significance of a correlation between two variables provides no information about the actual magnitude of that correlation (Fritz et al., 2012), effect sizes are necessary to present a holistic view of the relationship between two variables. Nominal-ordinal variables were analyzed using the also Chi$^2$-based Mann-Whitney U test, as all independent variables are dichotomous. Reported results include the number of observations n for the respective combination of variables, test statistic U, and the Z statistic as the standardized value of U. The latter is applicable because all n are sufficiently large (Nachar, 2008). For this reason, the reported p-value corresponds to a test of the Z-statistic and represents the level of asymptotic significance. Since the Mann-Whitney U test requires equal distributional shapes of the samples being compared to allow for a comparison of medians (Nachar, 2008), a Kolmogorov-Smirnov test was conducted beforehand. A significant Kolmogorov-Smirnov test result indicates that the distribution shapes of the answers to the ordinal variables differ significantly so that a significant Mann-Whitney U test result indicates differences in the overall distribution between the samples, not just the medians (Nachar, 2008). Variable pairs with significant Kolmogorov-Smirnov test results are marked in the respective tables and only interpreted with respect to their differences in answer distributions. The absolute value of r was calculated for effect size (Fritz et al., 2012). Again, only significant results with effect sizes of $r \geq 0.2$ are discussed, as effects below this value may be considered negligible.

### 2.3. Sample description

Compared to the average Bavarian farmer population (Table 1), the sample contains a larger fraction of organic farmers, which may be explained by the data being collected at events on digital hoeing technology, which is of particular interest to organic farmers due to their greater need for mechanical weed control. The survey participants are also better educated and younger than the average Bavarian farmer, which may create a pro-technology bias (Pierpaoli et al., 2013).

**Table 1**
Comparison of sample demographics ($n = 141–172$) with Bavarian average.

| Farm/farmer characteristic | | Sample | Bavarian average |
|---|---|---|---|
| Farm size | Mean | 104.8 ha | 35.3 ha[1] |
| | Larger than Bavarian average | 74.6 % | n/a |
| Occupational structure | Full-time | 73.9 % | 48.0 %[2] |
| | Part-time | 26.1 % | 52.0 %[2] |
| Farming system | Conventional | 73.0 % | 92.0 %[2,3] |
| | Organic | 27.0 % | 8.0 %[2,3] |
| Production branch | Cash crops | 80.1 % | 31.0 %[2, 4] |
| | Fodder crops | 48.1 % | 49. 7%[2, 4] |
| | Grassland | 59.3 % | |
| | Other | 28.0 % | 3.2 %[2, 4] |
| Technology use profile | Use of automatic steering system | 32.3 % | n/a |
| | Intent to invest in field crop robots | 22.2 % | n/a |
| Level of agricultural education | Agric. journeyman | 31.3 % | 71.2 %[5, 6, 7] |
| | Agric. master | 32.5 % | 18.4 %[5, 6, 7] |
| | Agric. technician | 5.5 % | 6.9 %[5, 6, 7] |
| | University graduate | 20.2 % | 6.7 %[5, 6,7] |
| | Other | 10.4% | n/a |
| Age | 19 years or younger | 2.3 % | 0.9 %[5, 6] |
| | 20–29 years | 41.9 % | 7.2 %[5, 6] |
| | 30–39 years | 15.1 % | 22.4 %[5, 6] |
| | 40–49 years | 15.1 % | 35.2 %[5, 6] |
| | 50–59 years | 20.9 % | 29.4 %[5, 6] |
| | 60 years or older | 4.7 % | 5.0 %[5, 6] |
| Gender | Male | 90.9 % | 92.6 %[5] |
| | Female | 9.1 % | 7.4 %[5] |

[1]StMELF (2018) [2]calculated based on LfStatD (2014b) [3]calculated based on Bayerisches Landesamt für Statistik (2018) [4]The Information was not available in the same categories. The present survey data allow naming of multiple categories. Data used for comparison groups farms based on contribution to overall farm income and also considers animal husbandry; 63.9% of farms in comparison data focus on a single branch of production. [5]Calculated based on Bayerisches Landesamt für Statistik und Datenverarbeitung (2014) [6]The information was not available in the exact age/education units applied in the questionnaire. [7]The percentages refer to a total of only the four named levels of education, as no information for 'other' was available.

Of those participants that indicated their farm size, 25.4 % operate farms smaller than the Bavarian average. The median farm size for smaller farms ($n = 35$) lies at 20 ha (range: 10–35.3 ha) while that of larger farms ($n = 103$) lies at 97 ha (range: 35.4–1,450 ha). A review of the postal codes indicated on the questionnaires shows that at least nine participants came from outside Bavaria and further 15 participants indicated no or only incomplete postal codes. These participants reported some of the largest farm sizes, including the overall maximum of 1,450 ha, which may explain why the sample's average farm size exceeds the Bavarian average: The federal state of Thuringia, which borders Bavaria and matched several of the largest farms' postal codes, has a much different agricultural structure than Bavaria for historical reasons. Given the applied method of analysis, re-coding farm size as a binary variable, these few large farms should not distort the results.

The presence of some vocational students at the events provides a reason for the strong representation of the 20–29 years age-bracket in the sample compared to the average Bavarian farmer population (Table 1) and the younger age of conventional as compared to organic farmers ($U = 1257.00$, $Z = -3.22$, $p = 0.001$, $r = 0.3$). These students are all trained farmers with work experience pursuing further education while working on or already managing a farm. Since employment and/or ownership status was not queried in the questionnaire, no statement can be made about the percentage of farm owners as opposed to employees or managers in the sample.

## 3. Results and discussion

### 3.1. Influences on the intention to invest in field crop robots

At the time of surveying, no participant had invested in field crop robots already, although 22.6 % plan to invest in the technology within the next five years. Only the farming system significantly influences participants' plans of investment in field crop robots (Table 2), with organic farmers intending to invest more often than the expected value and *vice versa* for conventional farmers. This rather strong difference between organic and conventional farmers may be explained by the need for mechanical weed control in organic farming and the increasing number of market-available robots specialized for weeding in recent years (Treiber et al., 2019).

The intention to invest in field crop robots can be expected to be influenced by the perception of advantages and disadvantages of the technology. Beginning with the evaluation of advantages (Fig. 3), 'reduced soil compaction' is viewed as the greatest asset of field crop robots, indicating an underlying assumption of robots weighing less than conventional tractors. Indeed, in the provided list of possible advantages, 'reduced soil compaction' as well as 'possibility of treatment of individual plants', 'possibility of intercropping', and 'preservation of small-scale landscape' were indicated to be pertaining only to small robots. In the ranking of perceived advantages, several economic advantages follow, pointing to the possible source of motivation in case a purchase of field crop robots is considered. 'Preservation of small-scale landscape' as a social aspect and 'possibility of treatment of individual plants' as well as 'possibility of intercropping' as agronomic techniques but also ecologically relevant aspects are ranked as less important

**Table 2**
Results of Pearson's Chi$^2$-Test of Independence between 'Intent to purchase field crop robots' and four independent variables.

| | Farm characteristic | n | Chi$^2$ | df | p | Phi |
|---|---|---|---|---|---|---|
| Intent to purchase field crop robots | Organic farming | 121 | 27.14 | 1 | 0.000*** | 0.5 |
| | Part-time farming | 138 | 0.55 | 1 | 0.814 | 0.0 |
| | Larger than Bavarian average | 116 | 2.22 | 1 | 0.137 | 0.1 |
| | Use of automatic steering system | 143 | 1.66 | 1 | 0.197 | 0.1 |

* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

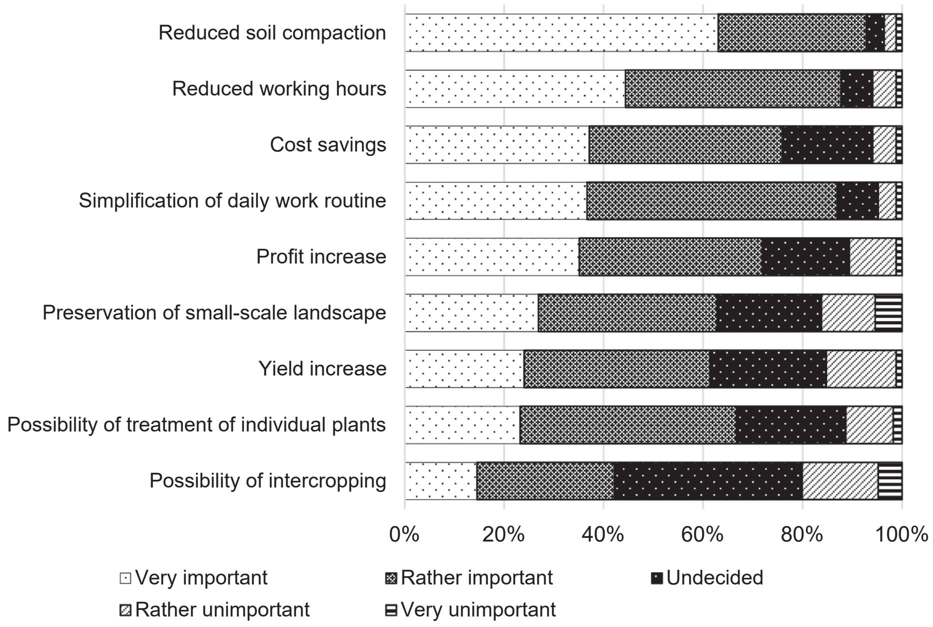

**Fig. 3.** Evaluation of possible advantages of field crop robots; n = 165–171 (source: own survey).

advantages by participants and may thus represent only secondary sources of motivation or be unfamiliar to participants as advantages of field crop robots.

Participants were further queried which aspects of robotics they perceive as hindering (Fig. 4). The results underline the status of field crop robots as a novel technology as ‘unresolved liability issues’ and ‘market maturity and availability of robots’ are considered most problematic.

Comparing these findings to the influences on adoption of autonomous agricultural technology in the literature, several similarities emerge. Rial-Lovera (2018) interviewed farmers and other agricultural experts in California, also finding cost reduction to represent a major driver of the adoption of robots in agriculture. The experts in her interviews point to a lack of labor availability specifically as an explanation for cost reduction through robots. This is also echoed in Rübcke von Veltheim and Heise’s (2020) expert interviews. The data presented herein do not provide participants’ view of labor availability, but the literature review confirms that labor scarcity is becoming increasingly relevant in the German agricultural sector. The present results on a ‘lack of compatibility with older technology’ being considered ‘very problematic’ or ‘rather problematic’ by a majority of respondents match the results of Rial-Lovera’s (2018) interviews, in which a lack of equipment compatibility and standardization is also voiced. Similarly in Australian farmer interviews conducted as a pre-study for the development of a field crop robot, Redhead et al. (2015) learned that a lack of compatibility represents a major impediment to farmers when adopting new or specialized technology. They also name reliability under changing conditions as a very important aspect, which is not covered in the present survey but also touched upon by Devitt (2018). The importance of economic factors such as ‘cost savings’, ‘simplification of daily work

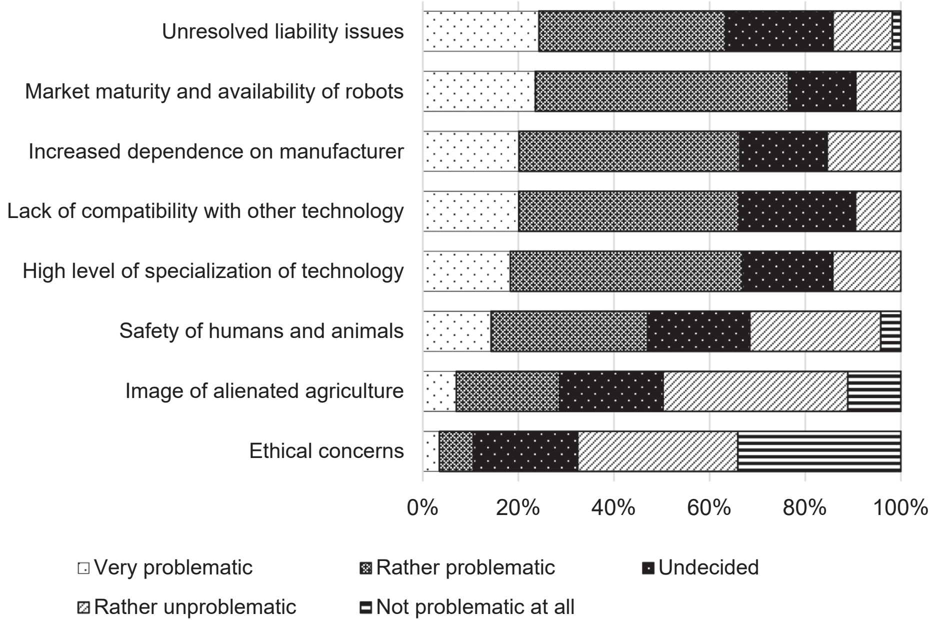

**Fig. 4.** Evaluation of possible disadvantages of field crop robots; n = 168–171 (source: own survey).

routine', and 'reduced working hours' to a majority of the present survey respondents, on the other hand, is confirmed by German manufacturers (Rübcke von Veltheim and Heise, 2020) and mirrored in the importance attributed to field crop robots for the tedious and thus expensive task of manual spot weeding or spraying by Australian farmers (Redhead et al., 2015). The clusters identified by Rübcke von Veltheim and Heise (2021) also indicate that a positive attitude toward field crop robots ('open-minded supporters' and 'convinced adopters' clusters) is associated with expected facilitation of work processes but not necessarily economic benefits. The two positively inclined clusters differ, however, with respect to their evaluation of more environmentally friendly production with the help of field crop robots, which is valued most greatly by the 'convinced adopters'. Conversely, environmental aspects as perceived advantages in the present survey ('reduction of soil compaction', 'possibility of treatment of individual plants', and 'possibility of intercropping') are not attributed equal levels of importance (Fig. 3) and do not correlate significantly with the 'intent to invest in field crop robots' (Table 3). This divergence in findings demands further research into the ecological dimension of farmers' acceptance of and investment in field crop robots. Finally, Devitt (2018) considerations on a loss of connection to one's farm and of social interactions during farm work cannot be directly reproduced in the present sample because of the phrasing of questions. Some experts in Rübcke von Veltheim and Heise's (2020) study, however, also state that farmers may be discouraged by no longer being fully in control, e.g. not being able to repair their own equipment. The present results show, though, that only a small group of participants are concerned about field crop robots creating an 'alienated image of agriculture' or raising 'ethical concerns' (Fig. 4). In addition to this descriptive, comparative analysis, some significant correlations of perceived advantages and disadvantages mostly with farm size, production system, and purchase intent could be identified (Table 3 and Table 4). Only significant results are presented in these and the following tables, but a complete listing of all test results may be found in the supplementary material.

Respondents from larger farms tend to be more focused on financial advantages of field crop robotics whereas small-scale farmers place more importance on environmental and social aspects. Large-scale farmers show a tendency to be more wary of 'unresolved liability issues' and 'safety of humans and animals' while also differing in their response distribution on the advantage of 'profit increase', suggesting that large-scale farmers may see the lack of clear laws on operating field crop robots (Vogel, 2020) as a higher financial risk. Conversely, small-scale farmers consider 'reduced soil compaction' somewhat more important than large-scale farmers. Given the existence of a strong correlation between small-scale farmers and part-time farmers in the sample (n = 134, Chi$^{2}$ = 51.63, df = 1, p < 0.000, Phi = 0.62) , similar effects for these two variables were expected. Instead, part-time farmers and full-time farmers differ only in their evaluation of 'preservation of small-scale landscape', which was deemed more important by part-time farmers. This distinction may point to different motivations for on-farm work between full-time and part-time farmers (cf. Mittenzwei and Mann, 2017) and suggests that size of the farm and size of the contribution of on-farm work to household income do have discrete effects on farmers' views of field crop robots.

**Table 4**
Mann-Whitney U-Test of perceived disadvantages of field crop robots and dichotomous independent variables.

| Perceived disadvantages | Farm characteristic | n | U | Z | p | r |
|---|---|---|---|---|---|---|
| Unresolved liability issues | Larger than Bavarian average | 133 | 1304.50 | −2.04 | 0.041* | 0.2 |
| Safety of humans and animals | Larger than Bavarian average | 132 | 1139.00 | −2.84 | 0.004** | 0.2 |
| Image of alienated agriculture | Intent to purchase field crop robots | 143 | 1245.00 | −2.50 | 0.013* | 0.2 |
| Ethical concerns | Intent to purchase field crop robots | 143 | 1158.00 | −2.97 | 0.003**$^{K}$ | 0.2 |

$^{K}$ = significant Kolmogorov-Smirnov Test, i. e. group distributions differ, hence Mann-Whitney U-Test refers to distribution instead of median.
* = p < 0.05, ** = p < 0.01, *** = p < 0.001.

The farming system influenced participants' views on 'reduced working hours' and 'possibility of intercropping', both of which were considered more important by organic farmers. Given the ban of most agrochemicals in organic farming, organic farmers may economize overproportionately by replacing high-cost manual labor with robotic weed control (Sørensen et al., 2005). Similarly, intercropping presents a way to reduce the need for pest and weed control as well as fertilizer by utilizing synergies between certain plant species. While intercropping is work-intensive to implement, it can be profitable and may reduce economic losses in weak years (Bybee-Finley and Ryan, 2018). Field crop robots may help tip the cost-benefit balance in favor of intercropping by reducing labor-related input costs, thus making intercropping economically more attractive and generating ecological co-benefits. The 'intent to purchase field crop robots' is also related to the perceived problem of creating an 'image of alienated agriculture'. Less than a fifth of survey participants intending to purchase field crop robot is thus concerned, compared to almost a third of those not planning to make such an investment. The groups differ similarly in the distribution of their evaluation of 'ethical concerns' as problematic. This presents an interesting point of further research, for example to investigate which aspects fuel these concerns and whether these concerns exert a conscious or unconscious influence on the intent to purchase.

### 3.2. *Preferences for size and type of robot*

Robot sizes are concomitant to certain functions, which may motivate participants' responses to the question discussed in the following. Participants clearly consider owning small field crop robots in ten years more likely than owning a large autonomous tractor (Fig. 5), although the 'intent to purchase field crop robots' within the next five years correlates with the evaluation of likelihood of ownership ten years into the future for both sizes (Table 5).

**Table 3**
Mann-Whitney U-Test of perceived advantages of field crop robots and dichotomous independent variables.

| Perceived advantages | Farm characteristic | n | U | Z | p | r |
|---|---|---|---|---|---|---|
| Reduced working hours | Organic farming | 138 | 1442.50 | −2.09 | 0.037* | 0.2 |
| Simplification of daily work routine | Intent to purchase field crop robots | 141 | 1315.50 | −2.36 | 0.018* | 0.2 |
| Profit increase | Larger than Bavarian average | 135 | 1324.00 | −2.26 | 0.024*$^{K}$ | 0.2 |
| Possibility of intercropping | Organic farming | 133 | 1168.00 | −3.04 | 0.002** | 0.3 |
| Preservation of small-scale landscape | Part-time farming | 158 | 1625.50 | −3.19 | 0.001** | 0.3 |
|  | Use of automatic steering system | 160 | 1845.00 | −3.47 | 0.001**$^{K}$ | 0.3 |
| Reduced soil compaction | Larger than Bavarian average | 132 | 1297.00 | −2.44 | 0.015* | 0.2 |

$^{K}$ = significant Kolmogorov-Smirnov Test, i. e. group distributions differ, hence Mann-Whitney U-Test refers to distribution instead of median.
* = p < 0.05, ** = p < 0.01, *** = p < 0.001.

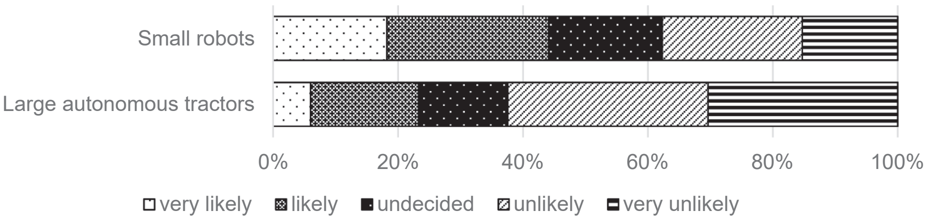

**Fig. 5.** Perceived likelihood of operating large or small robots on own farm in ten years; $n = 170$ (small), 168 (large) (source: own survey).

**Table 5**
Mann-Whitney U-Test of type of robot considered most likely on own farm in ten years and dichotomous independent variables.

| Robot ownership probability | Farm characteristic | n | U | Z | p | r |
|---|---|---|---|---|---|---|
| Probability of operating large autonomous tractors on own farm in 10 years | Intent to purchase field crop robots | 139 | 876.50 | −4.19 | $0.000^{***K}$ | 0.4 |
| Probability of operating small robots on own farm in 10 years | Intent to purchase field crop robots | 141 | 1068.00 | −3.25 | $0.001^{**K}$ | 0.3 |

$^{K}$ = significant Kolmogorov-Smirnov Test, i. e. group distributions differ, hence Mann-Whitney U-Test refers to distribution instead of median.
* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Although a majority of participants consider owning a large autonomous tractor themselves ten years into the future ‘rather unlikely’ or ‘very unlikely’, a significant and sizable difference in the response pattern exists between participants not intending to purchase a field crop robot and those already planning to invest in field crop robots within the next five years. The pattern for the future ownership of small robots is similar, though less pronounced, with those planning to invest in the near future consequently also considering the ownership of either type of robot more likely. However, as the question on the ‘intent to purchase field crop robots’ did not specify the size of the robots, those survey participants that indicated no ‘intent to purchase field crop robots’ may possibly have had autonomous tractors in mind more often, which Fig. 5 documents as being of less interest.

Participants also indicated which robot type, if any, they could imagine performing various agronomic tasks, from sowing to harvest. Despite small robots being considered more likely to be owned in the future overall, large autonomous tractors are considered more suitable for actual work on the field (Fig. 6), representing a distinctive contradiction. Only for one task, plant protection measures, do participants consider small robots more suitable than large autonomous tractors.

Particularly in the context of the general preference for small over large robots, this finding appears difficult to explain. Skepticism regarding market maturity of autonomous field vehicles (Fig. 4) may play a role as may the influence of a status quo bias regarding size, given the ever-increasing size of agricultural machines in recent decades. However, it is also conceivable that those who could imagine owning a small robot themselves in ten years (Fig. 5) had a weeding robot in mind as the likelihood of ownership of small robots and type of robot for plant protection measures correlate significantly ($n = 164$, $\text{Chi}^2 = 28.12$, $df = 12$, $p = 0.005$ (Monte-Carlo Simulation), Cramér’s $V = 0.2$).

This assumption is further supported by the number of already existing robotic solutions to replace hand-weeding, which Treiber et al. (2019) have identified as the largest category by far of currently or soon-to-be market-available field crop robots. The potential of robotic weeding may thus outweigh the skepticism toward autonomous technology. Testing for correlations with perceived advantages, ‘simplification of daily work routine’ and ‘possibility of treatment of individual plants’ were deemed ‘rather important’ or ‘very important’ by a large number of those considering small robots most suitable for plant protection measures ($n = 163$, $\text{Chi}^2 = 25.59$, $df = 12$, $p = 0.014$ (Monte-Carlo Simulation), Cramér’s $V = 0.2$ and $n = 163$, $\text{Chi}^2 = 21.89$ , $df = 12$, $p = 0.035$ (Monte Carlo Simulation), Cramér’s $V = 0.2$, respectively). Additionally, more than three quarters of participants who intend to invest in field crop robots consider the advantage ‘possibility of treatment of individual plants’ ‘rather important’ or ‘very important’ (cf. Table 3). Based on these correlations, albeit moderate, and the general preference of small robots for plant protection measures, small robots show potential to be accepted as a replacement for cumbersome and expensive tasks like hand-weeding.

Significant correlations between the choice of robot type for specific tasks and the independent variables could be observed only for a few cases (Table 6). The significant correlation between ‘organic farming’ and ‘mineral fertilizer application’ results from conventional farmers considering large autonomous tractors or both sizes most suitable, compared to both sizes or neither size for organic farmers. Although

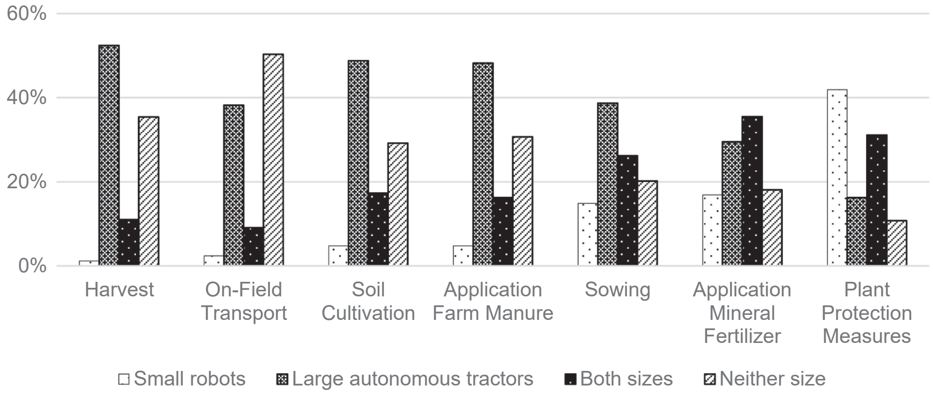

**Fig. 6.** Type of robot considered more suitable for various farm tasks in ascending order of choice of small robots; $n = 164–169$, (source: own survey).

**Table 6**
Pearson's Chi$^2$ Test of Independence for the type of robot, if any, for specific tasks and dichotomous independent variables.

| Agronomic task | Observed variable | n | Chi$^2$ | df | p | Cramér's V |
|---|---|---|---|---|---|---|
| Soil cultivation | Intent to purchase field crop robot | 141 | 9.71 | 3 | 0.021*$^{M}$ | 0.3 |
| Mineral fertilizer application | Organic farming | 133 | 8.24 | 3 | 0.041* | 0.2 |
| Harvest | Intent to purchase field crop robot | 138 | 7.66 | 3 | 0.043* | 0.2 |
| On-field transport | Intent to purchase field crop robot | 138 | 12.98 | 3 | 0.006**$^{M}$ | 0.3 |

$^{M}$ = exact test using Monte-Carlo simulation due to low expected cell counts.
* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

**Table 7**
Mann-Whitney U-Test of type of ownership considered most likely and dichotomous independent variables.

| Operation mode | Observed variable | n | U | Z | p | r |
|---|---|---|---|---|---|---|
| Individual purchase and operation | Organic farming | 137 | 1366.00 | −2.28 | 0.023* | 0.2 |
| | Use of automatic steering system | 161 | 2248.50 | −2.27 | 0.023* | 0.2 |
| | Intent to purchase field crop robots | 139 | 1196.50 | −2.49 | 0.013* | 0.2 |
| Organization by machinery ring | Part-time farming | 160 | 1899.50 | −2.22 | 0.026* | 0.2 |

* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

mineral fertilizer is not used in organic farming, 87 % of organic farmers in the sample chose to answer this question, indicating that they still wanted to express their opinion on this matter. Among those participants intending to invest in field crop robots within the next five years, small robots are not viewed as suitable for 'soil cultivation' or 'harvest', but instead large autonomous tractors or both sizes, respectively, can be imagined for these tasks. For 'on-field transport', those planning on investing in field crop robots are undecided, choosing both sizes more often than expected. However, almost half also indicate that they cannot imagine either type of robot despite intending to purchase field crop robots. This underlines the vagueness of the term 'field crop robots' when querying the intent to invest.

### 3.3. *Preferences for mode of operation of field crop robot*

In addition to traditional modes of operation, the dissemination of digital farming technologies including robotics is accompanied by a rise in offers of 'as a service' or 'service by manufacturer' options. Rather than selling the machine as product, the manufacturer acts as a contractor and uses the product to deliver a service. In the questionnaire, the options included individual, shared ('machinery group', 'machinery ring'), and service ('service by contractor', 'service by manufacturer') operation modes. Participants react most favorably toward traditional service and shared options (Fig. 7). The novel option 'service by manufacturer' is received only poorly.

Differences between large- and small-scale farmers as well as full-time and part-time farmers can be observed regarding the preferred mode of operation (Table 7). Part-time farmers show a tendency to be more inclined toward 'organization by machinery ring' of field crop robot deployment, which may be explained by the expected level of utilization. On the other hand, organic farmers tend to be more open to 'individual purchase and operation' of field crop robots than conventional farmers, despite the economy of shared or contracting options depending on the level of utilization (Sørensen et al., 2005). Finally, significantly different responses between users and non-users of automatic steering systems and those intending to invest in field crop robots compared to those not interested in doing so on 'individual purchase and operation' are evident. Participants already operating automatic steering systems or intending to purchase field crop robots are more positively inclined toward 'individual ownership and operation' of field crop robots than their respective counterparts.

## 4. Summary and conclusion

Revisiting the initial research questions to guide the exploration of the present data, the analysis yields useful results. While small field crop robots are generally preferred over large autonomous tractors for the operation on participants' own farms ten years into the future, survey participants clearly see plant protection measures as the main, if not only area of deployment thereof, preferring autonomous tractors or neither robotic solution in almost all other cases. While the sample at large prefers traditional non-purchase options for the operation of robots, those individuals open to an investment in robots favor an individual purchase. Novel 'as a service'-options were of little interest.

Informative correlations of perceived advantages and disadvantages further support these findings, though not all correlations match the existing literature. In particular, the importance of workload reduction for organic farmers further supports the case of small weeding robots. Although small field crop robots have been identified as potentially profitable for small farms in the literature, small-scale farmers in the present sample place comparatively less value on profit improvements from field crop robots. They do, however, consider reducing soil

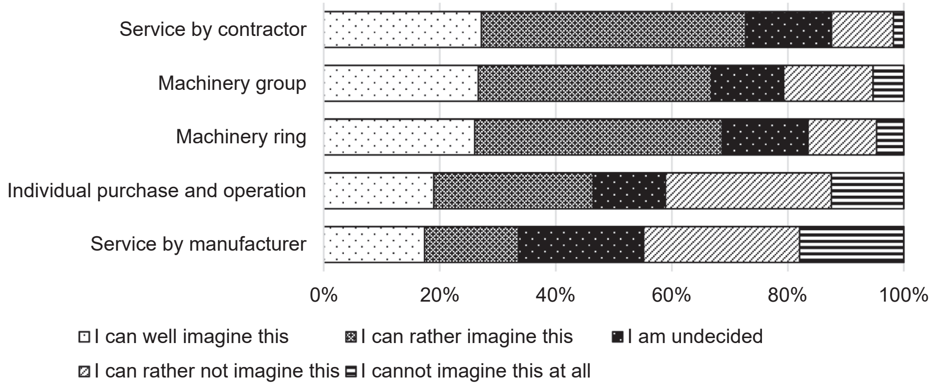

**Fig. 7.** Preferred mode of ownership and operation of field crop robots; n = 167–169 (source: own survey).

compaction more important than their larger counterparts. Small-scale farmers as a potential group of field crop robot buyers should therefore be informed better about the ecological benefits of field crop robots as well as the role of small robot scalability in economically maintaining small fields. Additionally, the potential of small robots for tasks other than crop maintenance should be emphasized where appropriate. Dissemination should focus on shared options to allow hesitant farmers to test the technology as lack of market maturity was named as a major obstacle to acceptance. Given that current users of automatic steering systems do not show a significantly higher intention to invest in field crop robots than non-users, prior purchase of this technology cannot be assumed to identify innovators or early adopters in the dissemination process of field crop robots.

Although the survey was administered in Bavaria, a federal state of Germany known for its small-scale agriculture, three quarters of participants at the field demonstration events exceed the average Bavarian farm size, indicating that the results do not represent the views of this federal state's predominantly small-scale farmers. The comparatively low attendance of small-scale farmers suggests that they may not view the presented technologies, including field crop robots, as realistic in their business context. This corresponds to the small-scale farmers that did attend being significantly less concerned with profit improvement through field crop robots than large-scale farmers. Large-scale farmers, conversely, in addition to being more numerous at the field demonstration and lecture events, are more concerned about economic and legal aspects of field crop robots, suggesting that they have already invested more time in learning about the details of field crop robot operation. These considerations underscore the need for better information among small-scale farmers, but also indicate that the group of innovators and early adopters of field crop robots will likely be composed of large-scale farmers.

The meaningful influences on farmers' stances toward field crop robots discovered despite these biases in the sample should be investigated in more detail and with larger, representative samples to confirm the preliminary conclusions drawn herein. As robot technology for crop farming is being further developed, changes in power source, means of locomotion, or level of specialization will influence technology acceptance and should therefore also be considered when comparing future research results. Additionally, investigation into the impact of field crop robots on the agricultural labor market may be particularly insightful. The restrictions on seasonal labor migration as a result of the Covid-19 pandemic underscored farmers' dependence on reliable and cheap labor during workload peaks. As the search for sufficient farmhands in Germany had already become more difficult during the past years despite the European Union's open labor market, seasonal farm labor is increasingly becoming the bottleneck of agricultural productivity. A comparative survey of farmers' views on field crop robots after this external shock of the pandemic to the labor and sales markets could provide interesting results. Analyses of the economic efficiency of field crop robots under special consideration of labor cost and reliability as well as their impact on the home economies of migrant workers should also be considered for future research.

## CRediT authorship contribution statement

**O. Spykman:** Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **A. Gabriel:** Conceptualization, Investigation, Writing - review & editing. **M. Ptacek:** Investigation, Data curation. **M. Gandorfer:** Conceptualization, Investigation.

## Declaration of Competing Interest

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

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## Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2021.106176.

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