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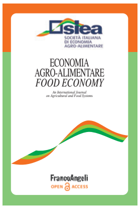

Balancing environmental benefits and agricultural technologies – perspectives from German consumers

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Abstract

Societal and political voices call for stronger environmental protection, biodiversity conservation, and reduced pesticide use. Integrating digital technologies into farming systems like strip intercropping offers promising pathways toward more sustainable and efficient food production. The successful adoption of these innovations depends on acceptance by both farmers and consumers. To explore these intersections of technology, sustainability, and market dynamics from a consumer perspective, a discrete choice experiment (DCE) followed by consumer segmentation was conducted in Germany in September and October 2023 (n = 2,022). The study examines preferences for different farming systems, focusing on autonomous machinery, landscape structure, food prices and environmental factors. Socio-demographic variables, along with value and attitude-based factors, were used to differentiate consumer segments. The study highlights social preferences for welfare-enhancing agricultural systems, such as strip intercropping, and demonstrates a societal demand for more sustainable agroecosystem outcomes, in terms of biodiversity, soil erosion prevention and reduced use of chemical pesticides. Results show that the balance between environmental benefits and agricultural technology differs markedly across four consumer segments, underscoring the need to integrate ecological and technological dimensions in communication and policy to enhance consumer acceptance and to support sustainable transitions in agriculture.

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Introduction

Germany's Sustainable Development Strategy underscores that achieving climate neutrality, resource efficiency, and longterm competitiveness requires a profound transformation of the economy and society, including agriculture and industry. To meet these goals, the strategy stresses the need for accelerated digitalization and automation, as efficient and sustainable digital infrastructures and technologies are seen as key enablers for innovative, low-carbon and resource-saving production and services (Die Bundesregierung, 2025). In this context, the 'twin transition' describes the simultaneous and interconnected shift towards an environmentally sustainable and more digital economy and society (Myshko *et al.*, 2024). It emphasizes that digitalization and sustainability should not be pursued in isolation but aligned so that digital technologies actively support environmental and social goals (for example climate neutrality, resource efficiency, and biodiversity protection). In agriculture, the twin transition means using digital tools to make farming more climate-friendly, resilient and resource-efficient (such as precision agriculture, IoT sensors, and AI-driven analytics, which enable optimized inputs like water, fertilizers, and pesticides), supporting environmental goals outlined in the European Green Deal while at the same time ensuring that digitalization itself follows principles of sustainable, fair and inclusive development (Myshko *et al.*, 2024; Brunori, 2022). Put differently, digital innovation is seen as an enabler of new forms of environmental, social and economic sustainability. One concrete example are small-scale diversified cropping systems as exemplified by (strip) intercropping (Vandermeer, 1989), which have been shown to deliver multiple environmental benefits. The main advantages of strip intercropping lie in increasing economic and ecological resilience: Paut *et al.* (2020) refer to economic risk reduction, while Gilley *et al.* (1997) mention the reduction of soil erosion. Chen *et al.* (2018) conclude that strip intercropping can be a successful adaptation strategy to water scarcity. Furthermore, positive effects on biodiversity are described (Brooker *et al.*, 2016). Measures to promote diversity and abundance of agricultural fauna also improve important ecosystem services such as natural regulation of pest organisms and pollination in agricultural ecosystems (Alarcón-Segura *et al.*, 2022; Albrecht *et al.*, 2020; Holland *et al.*, 2017). Moreover, intercropping systems increase the frequency and diversity of arthropods without significant yield losses (Brandmeier *et al.*, 2021).

However, small-scale diversification presents significant disadvantages regarding labor cost when using conventional agricultural machinery. Digital technologies, especially agricultural robotics, are attributed with the potential to offset these disadvantages, as the use of autonomous systems diminishes the importance of economies of scale (Lowenberg-DeBoer *et al*., 2019). Technologies such as artificial intelligence and robotics offer promising solutions for more sustainable and efficient food production (Ashwini *et al*., 2024). These advancements can also facilitate reduced pesticide use through targeted application and alternative pest management strategies (Gerhards *et al*., 2022). These innovations enable precise crop and resource management, potentially reducing costs and environmental impacts. Therefore, following the twin transition theory, field robots and other precision technologies are being investigated as potential enablers of strip intercropping and other small-scale diversified farming systems (Ditzler & Driessen, 2022; Sparrow & Howard, 2021; Spykman *et al*., 2023).

The adoption of these innovative approaches depends on various factors, including farmer acceptance (Spykman *et al*., 2021; Gabriel & Gandorfer, 2022), economic viability, but also consumer attitudes towards food commodities produced with different farming methods (Pfeiffer *et al*., 2020; Spykman *et al*., 2022; Wilmes *et al*., 2022; Zeddies *et al*., 2024). Society at its base is composed of individual people, each with their own needs, beliefs, and perspectives. Because of this diversity, it is essential to identify and understand different groups within the population. Recognizing these distinct groups allows for more targeted and effective communication, ensuring that messages resonate appropriately with each segment (Zeddies & Busch, 2025). Besides socio-demographic characteristics, consumer behavior can help distinguish consumer segments. The literature provides different value and attitude scales for typification of consumers in terms of food and ecological impacts of food production (Haws *et al*., 2014; Shimp & Sharma, 1987), but also regarding other attitudes, e.g., towards technology use (Edison & Geissler, 2003). Despite consumers often claiming that they would support more sustainable products, purchase numbers of those products do not reflect the expressed intentions. Terlau and Hirsch (2015) describe this 'attitude-behavior gap' as the discrepancy between consumers' expressed purchase intentions for sustainable products and their actual buying behavior, which is influenced by individual, social, and situational factors. They identify key barriers such as price, limited availability, information overload, habitual consumption routines, and psychological factors related to decision-making processes (Terlau & Hirsch, 2015). Consumer segmentation provides a promising approach to address this problem because it enables the identification of heterogeneous motivations, constraints, and contextual drivers across groups and the design of targeted intervention bundles (e.g., tailored messaging, incentive structures, product and distribution adjustments) (Schäufele & Janssen, 2023).

This study employs a discrete choice experiment, an established method in preference research, to explore the intersections of digital technology use, environmental effects, landscape, and consumer price sensitivity in agricultural products. The aim is to analyze consumer preferences and preference heterogeneity for different farming systems in Germany. The data were collected from September 22 to October 15, 2023, yielding a total sample of 2,022 respondents. The integration of indirect welfare dimensions, including environmental impacts and the form of agricultural management, into the discrete choice experiment combines several interdisciplinary perspectives. The extant literature on the valuation and consumer welfare provided by specific agroecosystems via choice experiments is still limited and fragmented. Alcon *et al.* (2020) is among the few studies addressing this topic. Unlike other studies applying consumer discrete choice experiments, which typically focus on product attributes such as taste, packaging, price, conventional, organic or local production (c.f. Bazzani *et al.*, 2017) or food product labels (c.f. Kolber & Meixner, 2023), and some additional information treatment (c.f. Jean *et al.*, 2025), this study concentrates on product attributes related to environmental impacts of specific agricultural practices. These attributes bear a resemblance to 'credence' attributes, which are characteristics of a product or service that consumers are often unable to verify or assess even after purchase and use. These attributes are frequently judged based on trust or belief (Fernqvist & Ekelund, 2014). Although Fernqvist and Ekelund (2014) identified some studies addressing credence characteristics related to production methods, these are primarily understood in terms of new preservation technologies or genetic modifications (GMO) and typically refer to specific products. From farmers' perspective with respect to agri-environmental aspects such as fertilizer use, application of pesticides, or restrictions on cropping, there have been a systematic review of over 120 discrete choice experiments studies forming a base on future design of possible agri-environmental programs (Schulze *et al.*, 2024). A more recent work examined Italian farmers' preferences for adopting agriculture 4.0 technologies using a choice experiment analysis (Fragomeli *et al.*, 2025). Therefore, a multitude of choice experiments have been conducted on the production side, addressing the adoption of agri-environmental applications or digital technologies. The contribution of the following paper is to bridge the gap to the demand side and to determine whether consumers, grouped by socio-demographic characteristics, values and attitudes, support a transition to different farming systems using a discrete choice experiment. The novelty of this approach is that consumer preferences are not determined by the choice of a specific product but are instead characterized by the attributes of agricultural cultivation and management practices associated with agri-food products. These attributes of agricultural production reflect a welfare-enhancing agricultural system in its entirety. A consumer segmentation analysis helps to identify different consumer types, providing a comprehensive understanding of consumer preferences which are useful for a successful implementation and communication for different farming systems such as strip intercropping.

Thus, the paper aims to capture the public's perspective and acceptance of alternative crop production systems with digital technologies (e.g., autonomous machinery) using a choice experiment, against the background of sustainability goals as described by the twin transition theory. In addition to the general consumer preferences regarding sustainable production systems, segmentation can partially explain the attitude-behavior gap by providing guidance for appropriate, targeted communication with different consumer groups enhancing acceptance for changes towards more sustainability. The remainder of the paper will describe the methodology, followed by the results of the choice experiment and the consumer segmentation, a discussion, and finally a conclusion.

1. Materials and methods

The discrete choice experiment was a component of a comprehensive online survey of German consumers (>17 years) that was conducted from September 22 to October 15, 2023. Access to a consumer panel was enabled through collaboration with a field service provider. Utilizing a consumer panel allows for the separation of personal data from content data, thereby ensuring adherence to research ethics. The panel facilitated a pre-stratification process to ensure that the sample was representative of the German population in terms of age, gender, size of residential area and federal state. In addition to various socio-demographic variables, data on personal connections to agriculture, as well as value and attitude scales for a typification of consumers were collected. Following data validation by eliminating speeders or straight-liners, the final survey sample consisted of 2,022 participants.

Discrete choice experiments (DCEs) are widely used to analyze consumers preferences in cases when the behavior of interest involves discrete responses or qualitative choice. They enable researchers to estimate the effects of attributes on preferences and are based on random utility theory (RUT) (Louviere *et al.*, 2008). RUT assumes that an individual q maximizes his utility, when choosing between J alternatives. Hereby, the utility U_{iq} of the i*th* alternative for the q*th* individual is composed of a systematic component V_{iq}, and a random, unobserved component ε_{iq} (Louviere *et al.*, 2000, Hensher *et al.*, 2015):

$$U_{iq} = V_{iq} + \varepsilon_{iq} \tag{1}$$

Typically, a DCE is composed of a set of choice sets, with each choice set composed of two or more alternatives. All alternatives in a choice set are defined by the same set of attributes, yet the expressed level per attribute may differ between choice sets. Consequently, a choice set provides survey respondents to choose between different combinations of attribute manifestations (or levels). When survey respondents are shown a choice set, they should select the alternative that most appeals to them. The process is iterated several times, with each choice set containing a different set of alternatives (Street & Burgess, 2007).

The choice experiment was part of an interdisciplinary joint research project by the Bavarian State Research Center for Agriculture (LfL) and the University of Passau which aimed to contribute to solving the challenges in biodiversity and soil conservation, economic competitiveness, and societal acceptance that the agricultural sector currently faces (www.future-crop-farming.de). Consequently, the attributes of the DCE were selected based on their anticipated environmental impact, such as effects on biodiversity and soil erosion (Alcon *et al.*, 2020), as well as their impact on agricultural management, including autonomous machinery. Therefore, the subsequent six attributes, accompanied by their respective levels in parentheses, were incorporated into the DCE:

- Biodiversity (less/unchanged/more).
- Soil erosion (less/unchanged/more).
- Chemical pesticide use (less/unchanged/more).
- Agricultural machinery (manned tractor/small autonomous robot/large autonomous robot).
- Landscape (strip intercropping/medium-sized fields/large-sized fields).
- Prices € 80/€ 100/€ 120/€ 140/€ 160) for cereal products, sugar, sweets, edible oils.

The base price for food groceries from specific agricultural crops (e.g., cereal products, sugar, sweets, edible oils) was derived from the German population's household goods basket divided by the average household size and was estimated to about 100 € monthly (Destatis, 2023). The fixed task (FT), which can be used for testing specific product configurations and internal validity (Sawtooth Software Inc., 2016), served as the key design for realistic scenarios regarding the attribute selection for the different farming systems (Figure 1): Combination 2 corresponds to the current status quo in

Bavarian agriculture: medium-sized fields with manned production (tractor) and unchanged environmental aspects in terms of biodiversity, soil erosion and the use of chemical pesticides at a base price of € 100. Combination 3 depicts a 'desired' target scenario, namely higher biodiversity, less soil erosion, and reduced use of pesticides. This could hypothetically be achieved through the strip intercropping approach and an autonomous large robot at an assumed higher product price of € 140 due to higher production cost. Combination 1 is an alternative future scenario with production on medium-sized fields by large autonomous robots. This would involve less pesticides, but more soil erosion and less biodiversity due to more intensive mechanical soil management. This scenario assumes that the negative effects of robots will not be mitigated through further technical development. The resulting consumer price for fixed task combination 1 is estimated at € 120, which is 20% higher than the base price.

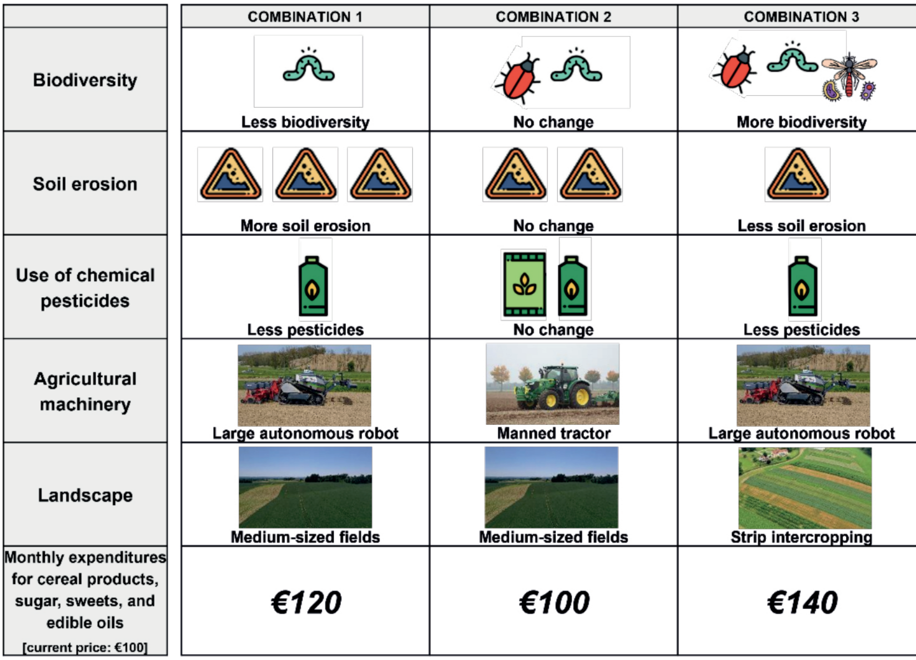
Based on the defined attributes and levels, a controlled random design with four questionnaire versions was generated using the random task generation method 'balanced overlap' in Lighthouse Studio 9.16.0 (Sawtooth Software Inc., 2024). Within the online survey pertinent images and icons were used to illustrate all attributes and levels for better visualization for the respondents (see Figure 1). At the beginning of the online survey, participants were randomly assigned to one of the four questionnaire versions and were provided with an explanatory passage translated from German.

Conventional food production can lead to environmental pollution, which can be reduced by changing the methods of production. Such site-adapted production methods enable for example a reduction of environmental risks by increasing biodiversity, protecting against soil erosion, less use of synthetic chemical pesticides, a more diverse landscape, and the use of modern and autonomous machinery. Below you will find three suggestions for combinations of farming systems, which, however, may also involve an increase in monthly expenditure on food (assuming the current base price for monthly groceries: € 100). Please indicate your preferred option in each case.

After this introduction, respondents had to choose six times between three different farming systems.

The DCE data were analyzed using Hierarchical Bayes (HB) modelling to estimate individual utilities for different farming systems. HB estimation techniques have become state-of-the art in marketing theory and practice to grasp individual heterogeneity in choice data (Goeken *et al.*, 2021; Voleti *et al.*, 2017). In addition, latent class analysis (LCA) was used to identify consumer groups with heterogenous preferences regarding farming systems.

Figure 1 - Example of a choice set (fixed task - FT) used in the DCE



The estimated HB model employs a hierarchical structure with two levels: An upper-level assuming a multivariate normal distribution for participants' part-worth utility values and a lower-level using a multinomial logit approach to analyze participants' probabilities of choosing specific attributes (Sawtooth Software Inc., 2021a). The model parameters are estimated through a Monte Carlo Markov Chain procedure, typically involving thousands of iterations to ensure robust results (Sawtooth Software Inc., 2021a). LCA was conducted to segment individuals based on response patterns and to identify subgroups with differing preferences. An optimal solution is achieved if the respondents' preferences are homogenous within one segment, but heterogenous between the segments. The latent class estimation process is iterative and involves the following steps: First, estimates of each segment's utility values are selected randomly. Next, each segment's estimated utility is used to fit each respondent's data and the relative probability that each respondent belongs to each segment is calculated. In the subsequent iterative process, the utility values of each segment and the probability of segment membership for each respondent are improved (Sawtooth Software Inc., 2021b). The optimal number of segments is determined using multiple fit criteria, including

Aikake Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood (Sawtooth Software Inc., 2021b). While the performance of these criteria can vary with sample size (Morgan, 2014; Nylund *et al.*, 2007), analyzing their relative changes helps identify the best-fitting model (Nylund-Gibson & Choi, 2018). When results are inconclusive based on these indicators, analysis of all candidate solutions is recommended to select the most interpretable one (Nylund-Gibson & Choi, 2018; Swait, 1994). Utilities between segments were compared using zero-centered differences, allowing for analysis of relative attribute importance and preference for specific attribute levels (Sawtooth Software Inc., 2021b).

Following the LCA, socio-demographic variables like age, education level, and income as well as three different factor scales of value and attitude-based typification served to differentiate the consumer segments. The following typification, which have been proven effective in the literature and have been extensively tested in studies, were used in the survey in the form of five-point Likert scales, ranging from 'strongly agree' = –2 to 'strongly disagree' = +2. This coding scheme indicates that negative values correspond to higher levels of agreement, and vice versa. Such tested items collectively interpret a 'latent' variable that, for example, establishes a specific value range for an individual. Using factor analysis, the responses to the individual items can be condensed into an individual standardized factor score and used as a metric predictor variable (Gabriel *et al.*, 2024):

- Green Consumption Value (GCV) with six items to reflect respondents' tendency towards environmentally friendly shopping behavior (Haws *et al.*, 2014).
- Consumer Ethnocentrism (CES) with four items to express consumers' preference for local and regional production (Shimp & Sharma, 1987; Jiménez-Guerrero *et al.*, 2014).
- Attitude towards technology (ATT) with nine items to measure openness towards new technologies and basic technical know-how (Edison & Geissler, 2003).

These three scales allow for a characterization regarding sustainable consumption, local food production and attitudes towards technology. HB and LCA analyses were performed using Lighthouse Studio 9.16.0 (Sawtooth Software Inc., 2024). LCA results were then transferred to SAS Studio 3.8 (SAS Institute Inc., 2023) for analysis of socio-demographic and attitude-based typification differences between segments. Socio-demographic variables were dummy-coded and tested for significant group differences using the Pearson Chi^2 Test. In case of a significant outcome (p-value < 0.1), pairwise Chi^2 Tests were carried out to identify which segments statistically differ from each other. For the not normally distributed attitude-based typification, the Kruskal-Wallis-Test (H-Test) was chosen to compare central tendencies of multiple independent samples (i.e., the identified segments). If the H-Test yielded a significant outcome (p-value < 0.1), the post-hoc Dwass-Steel-Critchlow-Fligner (DSCF)-Test helped identifying which segments differ statistically significant from each other.

2. Results

2.1. *Sample characteristics*

Table 1 shows the socio-demographic statistics for the total sample of 2,022 respondents in comparison to the German population (Destatis, 2024), confirming that the sample can be considered nationally representative in nearly all surveyed characteristics. Table 1 also illustrates the comparison of the four randomly selected survey subgroups for the discrete choice experiment regarding socio-demographic variables. The Pearson Chi^2 Test of independence reveals no p-value smaller than 0.05 for any considered variable, indicating that there are no significant differences between these groups. This confirms that the random assignment of survey participants to the subgroups was appropriate.

Table 1 - Distribution of socio-demographic variables in the randomly selected survey subgroups, total sample and the German population

Variable	**Categories**	**Randomly selected survey subgroups in absolute numbers**				**Total sample**	**GNS**[1]
		Group 1	**Group 2**	**Group 3**	**Group 4**	**%**	**%**
Gender	Female	253	256	249	288	51.7	50.6
	Male	236	251	230	251	47.9	49.4
	Non-binary	2	2	2	2	0.4	n/a
Age	18-30	87	93	75	88	17.0	21.2
	31-40	80	87	84	97	17.2	17.7
	41-50	70	74	90	95	16.3	16.2
	51-60	115	117	89	110	21.3	20.7
	≥61	139	138	143	151	28.2	24.3
Income	<1,000 €	49	49	66	66	11.4	8.6
	1,001-2,000 €	140	134	114	149	26.6	24.7
	2,001-3,000 €	107	120	119	119	23.0	23.5
	3,001-4,000 €	77	93	87	113	18.3	16.2
	4,001-5,000 €	65	55	51	48	10.8	10.8
	>5,000 €	53	58	44	46	9.9	16.1

Level of education	No qualific./SNVQ[2]	70	59	64	80	19.9	22.2
	Secondary school VQ[3]	144	151	136	167	43.5	43.1
	High school (Abitur)[4]	122	138	111	132	36.6	34.7
	Vocational training/univ.[5]	155	161	170	162		
Inhabitants (size of residence)	<5,000	68	68	71	73	13.8	13.0
	5,001-20,000	130	118	122	141	25.3	24.9
	20,001-100,000	128	148	136	148	27.7	27.3
	>100,000	165	175	152	179	33.2	34.8
	n	491	509	481	541		

[1] GNS: German national statistics (Destatis, 2024). [2] SNVQ = Secondary school non-vocational qualification, corresponds to the German 'Hauptschulabschluss' (low education); [3] VQ = Vocational qualification, corresponds to the German 'Mittlere Reife'; [4] High education. [5] Comparison with national statistics not possible, only limited to the previous three education categories.

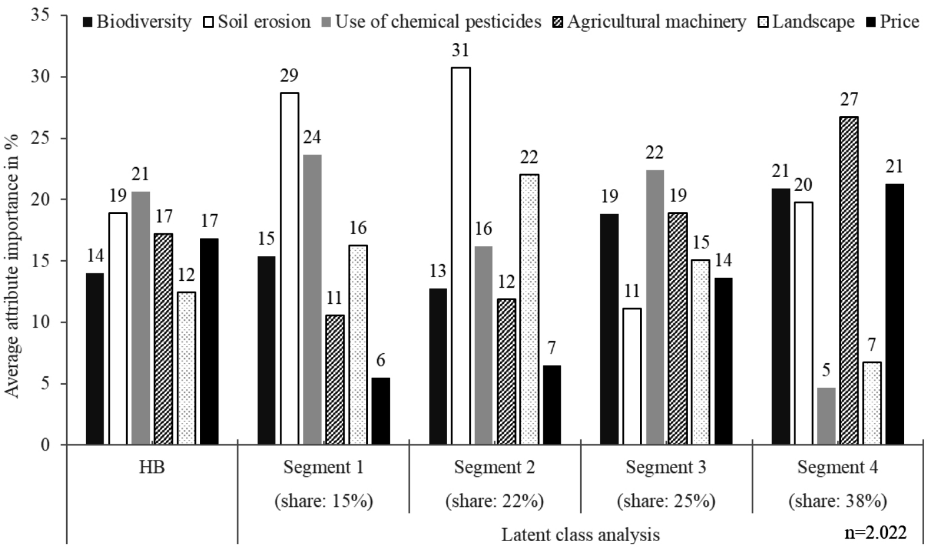
2.2. *Attribute importance and latent class analysis*

The estimated HB model has a mean root likelihood (RLH) of 0.675 which can be considered as good (Sawtooth Software Inc., 2021a). To identify the number of segments in the LCA, various fit criteria (AIC, BIC, Log-Likelihood) were checked. Their values suggested the four-segments solution as appropriate because the improvements in these criteria were particularly large from the three- to four-segments solution. The comparison of the four- and five-segments solution resulted in no substantial improvements or even deterioration of the criteria. For this reason, the four-segments solution was screened for interpretability (Swait, 1994). It proved to be reasonably interpretable and was therefore selected for further analysis. The shares of the four-segments solution are as follows: 14.9% for segment 1, 22.1% for segment 2, 25.0% for segment 3, and 38.0% for segment 4.

Figure 2 illustrates the results of the attribute importance from the HB estimation and the latent class analysis. The importance of the individual attributes is determined based on the range of the part-worth utility values (difference between the highest and lowest) of one attribute and sums up to 100% across all attributes. The larger the range, the more important the attribute is for preference formation. The HB estimation shows that the use of chemical pesticides is attributed to the highest importance on average at 21%, closely followed by soil erosion (19%). Both price and agricultural machinery follow at 17% each. Biodiversity and landscape receive slightly less importance compared to the aforementioned attributes, at 14% and 12%, respectively. In addition, Figure 2 illustrates differences in the attribute importances of the identified segments. Segments 1 and 2 consider soil erosion to be the most important characteristic. At the same time, consumers in these segments place less importance on the price compared to the other segments.

Segments 1 and 3 attach great importance to the attribute use of chemical pesticides. Segment 2 finds the attribute landscape more important than the other segments. The most important attribute for the largest segment 4 is agricultural machinery, followed by biodiversity and the price attribute. The use of chemical pesticides, on the other hand, is not decisive for segment 4. Segment 3 also reveals a high importance for agricultural machinery and biodiversity but places less importance to the attribute soil erosion.

Figure 2 - Average attribute importance for HB and latent class analysis in %



2.3. *Part-worth utilities*

A further analysis identifies the average relative part-worth utilities from the HB estimation for the respective attributes of the total sample and the four identified segments (Table 2). All part-worth utilities of an attribute add up to 0 as effects coding is used. Accordingly, positive values represent a higher part-worth utility within an attribute in relation to the other (negative) attribute levels; the respective highest part-worth utility for each attribute and each segment is printed in bold-face in Table 2. On average, participants perceive a higher relative utility from more biodiversity, less soil erosion, and less use of chemical pesticides than for the respective opposite levels or the status quo (i.e., no change). Similarly, for the technological aspect, the manned tractor receives a higher part-worth utility than the two autonomous robots at almost equal negative part-worth utilities. Regarding the landscape, consumers perceive a higher relative part-worth utility in strip intercropping than in large or medium-sized fields.

Table 2 - Part-worth average utility values of attribute levels (zero-centered difference)

Attribute	**Level**	**HB**	**Segment**			
			1	**2**	**3**	**4**
Biodiversity	Less (–)	–28.06	–40.82	–47.40	34.13	–54.56
	No change (=)	7.02	–10.47	18.51	**39.40**	–16.32
	More (+)	**21.05**	**51.29**	**28.89**	–73.53	**70.88**
Soil erosion	Less (–)	**49.18**	**72.50**	**66.18**	17.14	**78.34**
	No change (=)	–5.20	27.06	52.06	–41.99	–40.10
	More (+)	–43.98	–99.57	–118.24	**24.85**	–38.24
Use of chemical pesticides	Less (–)	**38.30**	**67.59**	–4.98	**74.91**	2.59
	No change (=)	10.65	6.65	**51.04**	–15.34	**12.64**
	More (+)	–48.96	–74.24	–46.05	–59.57	–15.23
Agricultural machinery	Manned tractor	**59.11**	**35.88**	**43.86**	**64.47**	**98.95**
	Large autonomous robot	–29.24	–27.46	–27.27	–49.02	–37.72
	Small autonomous robot	–29.87	–8.42	–16.59	–15.45	–61.22
Landscape	Large-sized fields	–19.56	–15.38	–55.30	**30.86**	–19.42
	Medium-sized fields	2.26	**56.53**	–21.47	–59.70	**21.06**
	Strip intercropping	**17.31**	–41.15	**76.77**	28.84	–1.64
Price		–122.92	–41.23	–48.73	–102.14	–159.48

For segments 1, 2 and 4, a reduction in soil erosion is preferred compared to the status quo or a higher soil erosion. While the first two segments are the least price-sensitive ones, the largest segment 4 has the most negative utility value for price. A high utility from more biodiversity is also evident in segments 1, 2 and 4 compared to the other respective levels. Segment 3, on the other hand, prefers the status quo of biodiversity. Regarding chemical pesticides, segments 2 and 4 prefer the status quo over 'less use'. Conversely, segments 1 and 3 clearly prefer less use of chemical pesticides. All segments have a high preference towards traditional use of machinery with a manned tractor. Strikingly, segment 4 is less opposed to large autonomous robots than to small autonomous ones. In the other three segments, the pattern is reversed. Segment 2 is the only segment which prefers strip intercropping compared to large- or medium-sized fields. Segment 3 seems indifferent between large-sized fields and strip intercropping but rejects medium-sized fields. Segments 1 and 4 draw a higher utility from medium-sized fields compared to the other two landscape options.

2.4. *Segment characterization*

Table 3 presents the socio-demographic composition of the four segments, highlights differences between them, and aids in their characterization. Statistically significant differences between the segments arise from age (younger or older than 40), level of education (secondary school or lower vs. vocational training, high school or higher), disposable income (less or more than 4,000 €), farmers in the personal network, and all three attitude-based typification. By contrast, no significant differences are observed for gender (male vs. female), size of place of residence (number of inhabitants lower or higher than 20,000), or whether respondents have experience in agriculture or a related sector. For the attitude- and value-based scales, mean scores per segment are displayed and negative values reflect higher approval. These scales range from –2, reflecting highest approval to the respective attitude, to +2, reflecting lowest approval to the respective attitude. In case of a significant outcome of the Chi^2 Test for the dummy-coded variables, pairwise comparison between segments is conducted in the same manner. For the attitude- and value-based scales, the post-hoc DSCF in case of significant outcomes of the non-parametric Kruskal-Wallis-Test allow for segment comparisons.

Segment 1 is characterized by younger respondents with a higher education, and the highest share of respondents who reported to have farmers in their personal network among all segments. Segment 1 comprises individuals with above-average technical affinity (ATT) and a high commitment towards green consumption (GCV). Segment 2 is comparable to segment 1 with regard to education levels and the presence of farmers in participants' personal networks. However, participants in segment 2 have the highest disposable income among all segments. Besides a high valuation of 'green consumption', like segment 1, segment 2 also considers regional

Table 3 - Dummy-coded socio-demographic composition of segments and test statistics for segment comparison

		Segments (shares in %)				Chi² Test statistic
Variable		**1**	**2**	**3**	**4**	**(p-values)**
Gender	Male	46.8	47.2	48.0	49.6	1.01 (0.7982)
Age**	<40 years	40.2[b]	34.4[ab]	29.8[a]	34.5[bc]	9.13 (0.0276)
Level of education***	Lower education	36.5[a]	39.4[a]	48.4[b]	44.3[b]	14.1 (0.0028)
Inhabitants (size of residence)	≤20,000	42.5	37.8	39.7	38.1	2.17 (0.5382)
Income*	<4,000 €	79.4[ab]	75.4[a]	82.2[b]	79.4[ab]	6.76 (0.0799)
Experience in agricult. or rel. sector		10.3	8.5	8.1	9.1	1.25 (0.7400)
Farmers in personal network***		23.9[b]	22.2[b]	14.8[a]	18.1[a]	13.73 (0.0033)
		Segments (mean scores)				**H-Test**
Attitude- and value-based scales		**1**	**2**	**3**	**4**	**(p-values)**
ATT***		–0.07[a]	–0.02[a]	0.17[b]	–0.07[a]	18.39 (0.0004)
GCV***		–0.19[a]	–0.19[a]	0.31[b]	0.06[c]	106.67 (<.0001)
CES***		–0.11[ac]	–0.24[a]	0.21[b]	0.04[bc]	36.75 (<.0001)

Significance level Chi² and Kruskal-Wallis-Test (H-Test): <0.1*, <0.05**, <0.01***. Pairwise Chi² and DSCF post-hoc Tests: segments with the same superscripts [a, b, c] do not differ significantly from each other. Attitude and value-based scales: negative values reflect higher approval.

production (CES) highly relevant. Next, segment 3 shows the most significant differences in pairwise comparisons with the other segments. It is composed of predominantly senior individuals and is characterized by the lowest levels of education and disposable income compared to the other segments. Significantly fewer participants in segment 3 have farmers in their personal network than in segments 1 and 2. All attitude- and value-based scales have positive values in segment 3, indicating the lowest commitment towards green consumption and local production as well as lower levels of technological affinity relative to all other segments. Segment 4, finally, is characterized by an average level of education and a strong affinity towards technology. However, its members do not show a strong commitment towards 'green consumption' and regionality.

3. Discussion

Similar to Alcon *et al.* (2020), the study at hand investigates social preferences for welfare-enhancing agricultural systems, such as strip intercropping, and demonstrates a societal demand for more sustainable agroecosystem outcomes in terms of biodiversity, prevention of soil erosion, and reduction of chemical pesticide use. In addition, different management options, including farming systems and autonomous machinery, are also examined. The relative importance of the six attributes analyzed in the DCE ranged from 12% for landscape to 21% for chemical crop protection, implying that society recognizes multiple dimensions of farming systems as relevant. Using latent class analysis, four distinct segments with marked differences in attribute importance and part-worth utilities were identified.

Concerning the attitude-behavior gap, results might be more biased towards a more environmentally friendly agricultural production (e.g., less use of chemical pesticides, more biodiversity) than consumers would support. However, the study was more focused on scenario analyses (e.g., using Hierarchical Bayes modelling) relying on part-worth utilities rather than willingness-to-pay assumptions. This procedure reduces sensitivity to design errors and improves validity for heterogeneous preferences (Hein *et al.*, 2022). In addition, the performed segmentation can partially reduce the gap by aligning measures with the specific barriers of each segment (e.g., knowledge deficits can be addressed by education). Still, the attitude-behavior gap cannot be closed by information provision alone, since situational, structural and psychosocial barriers also strongly shape behavior (Sheeran, 2002; Kollmuss & Agyeman, 2002). Segmentation therefore is not a panacea, but it increases the relevance and costeffectiveness of policy and market interventions by matching them better to the needs and levers of distinct consumer groups (Schäufele & Janssen, 2023).

The preferences for the use of autonomous machines in the production of grocery commodities, such as large and small autonomous robots, are lower compared to conventional manned tractors in all identified segments. Wilmes *et al.* (2022) observed similar reservations, as the use of digital technologies negatively impacted willingness-to-buy from the corresponding farms in their study. However, the authors found that the relationship turned positive when introducing environmental arguments. On the other hand, Zeddies *et al.* (2024) found attitudes towards agricultural robots generally positive among the German public, with information about possible environmental benefits increasing those positive perceptions. The strong preference towards 'traditional' image of farming suggests a general lack of visibility of autonomous agricultural technology in the public sphere (Pfeiffer *et al.*, 2020) and does not necessarily imply a general rejection of field robots. To counteract this, positive environmental impacts of robots and a consumer-friendly information strategy could enhance public trust in these technologies (Wilmes *et al*., 2022; Zeddies & Busch, 2025).

The findings further underscore that consumer acceptance of sustainable farming systems is shaped not only by ecological objectives but also by the framing of attributes and socio-environmental experiences, both of which merit closer attention in the design of policy and communication strategies. Thus, the balance between ecological objectives and technological innovation is perceived very differently across consumer groups. The identified consumer segments 1 and 4 might view technologies such as field robots as promising solutions. Segment 3, conversely, might associate them with risks, e.g., for the 'institution' of family farming and job security in agriculture (Zeddies & Busch, 2025), or prioritize environmental considerations and cost-related aspects instead. These heterogeneous perceptions underscore that the societal acceptance of agricultural innovation cannot be taken for granted and depends strongly on how tradeoffs are framed in public discourse.

Finally, the implementation of the twin transition theory in agriculture highlights significant tradeoffs between advancing sustainability goals and deploying digital technologies. In farming contexts like crop cultivation, rapid adoption of precision agriculture tools such as GNSS-guided tractors and drone-based monitoring entails substantial upfront material and energy costs from manufacturing and installation, alongside supply-chain impacts like rare earth mineral extraction, which may partially offset anticipated sustainability gains from optimized inputs (Brunori, 2022). These tradeoffs manifest along temporal, spatial, and societal dimensions, as highlighted in Myshko *et al*. (2024) on the twin transition in agri-food systems: A discrepancy exists between the temporal fluctuations in emissions resulting from the implementation of digital and mechanical infrastructure and the potential for long-term reductions in resource utilization, including water and mineral fertilizers. Spatially, localized environmental pressures – for example, soil compaction from heavy machinery or the accumulation of electronic waste – may contrast with aggregate reductions in greenhouse gas emissions at regional or global scales. Societally, the diffusion of digital technologies in agriculture tends to be skill-biased, privileging farmers with higher levels of digital literacy and education. This has the potential to result in the exclusion of more vulnerable groups from the benefits of the twin transition.

Conclusion

The results of the DCE indicate that strategies for introducing new farming technologies and different farming systems, such as strip intercropping, must consistently emphasize their confirmed or anticipated environmental benefits in order to foster legitimacy and social acceptance. The introduction of these innovations into agriculture therefore requires more than merely demonstrating efficiency gains; it also depends on clearly linking them to ecological improvements and broader societal goals. In practice, this calls for target group specific policy and communication strategies, as societal acceptance of sustainable and digital technologies is segment-dependent and cannot be achieved through uniform measures. Tailored information campaigns, transparent labeling, and cocreation formats, such as on farm demonstrations, field days or living labs, can help connect visible changes in production practices to tangible ecosystem outcomes and thereby strengthen public support. The observed reservations toward autonomous machinery imply that policy initiatives on technology must be accompanied by proactive communication about their environmental and social implications, including issues of occupational safety, labor displacement, and data governance. Finally, the discussion of twin transition tradeoffs indicates that digitalization policies should be systematically integrated with environmental policy and with measures that promote regional development and social inclusion, to avoid exacerbating spatial and socioeconomic disparities. This includes investing in rural digital infrastructure, strengthening independent advisory systems, and ensuring that support schemes do not disproportionately favor large, capital-intensive farms with high digital readiness. From a theoretical perspective, the study contributes to the literature on technology acceptance and sustainable consumption by jointly modeling ecological and technological attributes within a discrete choice experiment. It relates to the acceptance of agricultural innovation from a multi-dimensional perspective, thereby extending existing models that focus predominantly on either environmental or technological factors in isolation. Moreover, the estimated preference structures can serve as a basis for deriving willingness-to-pay in future studies, providing more concrete insights into societal willingness-to-pay for sustainable and digital technologies. However, it is important to acknowledge several limitations to this study. First, as is typical of most choice experiments, the results are based on stated rather than revealed preferences, which may overstate support for environmentally friendly options and underrepresent situational constraints in real purchasing contexts. Second, the study focuses on a specific national and cultural context and a limited set of attributes, which restricts the generalizability of the segment structure and preference patterns to other countries or technological configurations. Given the context- and time-dependency of preferences, as well as the rapid advancements in digital technology, further studies are necessary to achieve a more profound understanding of the evolution of societal acceptance of different farming systems. This understanding is imperative for the formulation of effective strategies to promote the adoption of sustainable and digital farming practices.

Declaration of generative AI use

During the preparation of this article, the authors used Perplexity, and DeepL Write to improve grammar and language and to search for available literature. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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