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Seeds of Industry Sustainability: Consumer Attitudes towards Indoor Agriculture Benefits versus Its Advanced Technology

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Abstract: Indoor agriculture (IA) mitigates, to some extent, global problems such as increasing demand for food and limited natural resources. Though the potential benefits of IA as a sustainable agricultural production method are widely discussed, the success of the industry depends on consumer acceptance of IA innovative technology and their willingness to consume leafy greens produced under this technology. Using cluster analysis, four distinct groups of U.S. leafy green consumers were identified: "IA Skeptics", "IA Open", "IA Supportive", and "IA Engaged". A strong positive consumer cluster emerged with no evidence of an existing cluster of consumers who could be referred as "Knowledgeable Rejectors", often found from the studies of consumer acceptance for novel food technologies. We concluded that, overall, U.S. leafy green consumers are ready to accept IA produce, but a significant number of consumers are yet to clearly decide on their attitude towards IA technology. Based on the evidence found from this study, we identified market opportunities for the IA industry with consumers of leafy greens given their broad willingness to consume IA produce and suggest marketing strategies to expand consumer awareness and acceptance of IA produce.

Keywords: indoor agriculture; innovation in food technology; consumer attitudes; cluster analysis; market segmentation

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1. Introduction

Indoor agriculture (IA) has been discussed as a potential solution to global issues such as addressing food insecurity and developing environmentally sustainable ways of growing crops [1–4]. Similar to greenhouses, which also fall under the umbrella definition of controlled environment agriculture (CEA), IA systems can have the unique ability to create an ideal environment for plant growth, with the potential to improve output quality while optimizing the use of inputs. The lines drawn among IA, vertical farming (VF), plant factory with artificial lighting (PFAL), and greenhouse as different CEA farming systems are not without controversy [5]. This article adopts a narrower definition of IA consistent with the requirements of the grant funding that supported the research. IA stands apart from greenhouses with the unique use of completely artificial lighting systems, which allow for growing crops within sealed structures, where the cropping areas are stacked vertically and the environment factors affecting plant growth are fully controlled. Although many high-tech greenhouses also adopt complex environment control systems and some supplemental artificial lighting, greenhouses remain open to the external environment to use some natural sunlight and related heating/cooling effects, which preclude total control and using multiple levels of growing shelves [6–8]. IA, therefore, expands its potential benefits to include efficient use of land and to encourage economic development in urban areas. As such, IA is viewed as a potentially significant contributor to the future of agricultural production methods by both researchers and policy makers [4,9]. In parallel with research developments, the IA industry has grown at a fast pace in the United States and abroad [10–13].

The aforementioned strand of literature and market reports commonly point out economic sustainability as one of the major challenges for IA farms to be successful. Compared to conventional field farming, IA farms require a large initial capital investment and expensive operational expenditure requirements [5,14], in particular specialized labor and the energy required to operate lighting and HVAC systems. One possible way to ensure the economic sustainability of IA is taking advantage of its unique ability to enhance product quality attributes and, consequently, augment revenue. With complete control over the environmental factors affecting plant growth rates and plant characteristics, IA enables plant growers to create or improve various attributes of leafy greens. For example, with ideally designed IA systems, growers could enhance the appearance, taste, or nutrient levels of leafy greens by controlling the lighting spectrum, intensity, and duration, as well as other environmental factors such as CO_2 level, air temperature, and humidity [15,16].

There is, therefore, a possibility of creating a differentiated product by adopting IA production systems, which can attract a premium price, potentially making IA growers price-makers, rather than price-takers in the leafy green market. Following the traditional search, experience, and credence (SEC) framework [17,18], the potential of IA systems is not limited to controlling the search or experience attributes of the product such as the appearance, taste, and nutrient levels, but it is extended to offering credence attributes. If an indoor farm building is located in an urban area, as claimed by Despommier [2], a grower would be able to directly provide urban consumers with "locally-grown" fresh crops in a year-round fashion. Furthermore, IA production systems carry an important contribution to environmental sustainability, as they save water by up to 95% and achieve 100-times higher productivity per land area than field farms [9].

The main objective of this paper is to investigate the level of consumer acceptance of IA produce given its novel technology. Identifying consumer acceptance of IA systems is particularly important to consolidate price premia and improve the profitability of IA because novel food technologies often face rejection by consumers on the market [19–21]. Since IA systems can be viewed as an aggregate of cutting-edge technologies, consumers may regard IA as an artificial or unnatural way of growing crops. This perception might intensify as IA provides consumers with produce that shows unexpectedly improved quality. The case of genetically modified food technology is an example of consumer rejection against novel food technology [22,23]. Even if not new to consumers, sometimes, certain growing methods can also raise public rejection. Organic foods, for example, generally obtain a high premium on the market according to the previous studies about the willingness to pay for organic foods [24,25], but even organic produce sometimes faces rejection by consumers [26,27].

There has been a strand of literature investigating consumer acceptance of IA produce, but the findings have sometimes been inconsistent [28–32]. Coyle and Ellison [28] and Nishi [31] estimated the willingness to pay a premium for vertically farmed lettuce using an experimental auction method, and they found no meaningful premium for the IA produce as an alternative to conventionally grown produce—field- or greenhouse-grown. Coyle and Ellison [28] found that consumers perceive vertically grown lettuce as less natural compared to lettuce grown in greenhouses or on field farms. On the other hand, Kurihara et al. [30] collected consumers' willingness to pay in a survey questionnaire and reported that up to a 40% premium for "factory-produced" vegetables over outdoor-grown vegetables was acceptable. While these conflicting results serve as evidence of heterogeneity among consumers, this also emphasizes the need for a study using a dataset large enough to serve as a representative sample of the U.S. consumer in order to determine industry pathways to sustainability. Coyle and Ellison [28] used a sample of 116 participants from the University of Illinois campus and surrounding community, while Nishi [31] used 116 non-student participants. Kurihara et al. [30] studied housewives residing in Tokatsu Region. Yano et al. [32] investigated Russian consumers' attitude towards IA produce in relation to demographic characteristics and opinions about the vegetables. They found attitude heterogeneity by eliciting consumers' favorability towards vertically farmed vegetables, analyzing the words from survey participants' text responses. This strand of literature strongly implies the existence of attitude heterogeneity towards IA among U.S. leafy green consumers. Based on this, we hypothesized that we would observe heterogeneity in the attitude towards IA produce across the sample that represents U.S. consumers as we estimated consumer acceptance of IA produce.

The second objective of this paper was to examine if there is a significant share of accepting consumers to support the economic sustainability of the industry and identify determinants of consumer attitudes. To perform this examination, the U.S. IA industry needs a consumer acceptance study focused on understanding the segmentation of U.S. leafy green consumers in terms of attitude towards IA and the characteristics of consumers. This paper identified consumer clusters in terms of attitude towards IA allowing for attitude heterogeneity among leafy green consumers. Principal component analysis (PCA) and cluster analysis (CA) were initially applied to identify clusters, then an ordered logit model (OLM) was used to investigate how the acceptance of IA produce varied between clusters. The OLM tests the hypothesis that the degree of acceptance of IA produce will vary by different consumer clusters. By doing so, we tested the difference across clusters, not only using attitude variables, but also using the acceptance variable. We also investigated the likelihood of being in specific attitude groups, which would be represented by different clusters, by using a logit model (LM) and taking into account potential candidate predictors of attitude towards IA produce. We hypothesized that determinants of consumer attitudes towards IA as a novel food technology are based on socio-demographic characteristics, vegetable purchase behavior, and opinions about relevant attributes, following previous literature [29,33–36].

This article contributes to the literature on IA in several ways. First, unlike past research using limited samples, consumer acceptance of IA produce was measured with an extensive and representative sample of U.S. leafy green consumers. Its conclusions are thus more robust and empirically supported. Second, it confirmed consumer behavior's systematic heterogeneity by discovering four different consumer clusters based on attitudes towards IA produce, purchasing behavior, and demographics. Finally, it presents potential predictors for cluster membership that can be useful for the U.S. IA industry to design marketing and production strategies that meet the needs of well-defined consumer segments.

2. Consumer Attitude Data

The consumer survey data for this study were collected between July and August 2021. All questions asked in this survey and relevant to our analysis are reproduced verbatim through the manuscript. The distribution of the survey was conducted through the online survey vendor Qualtrics. The target sample was leafy green consumers who were over 18 years old and living in the United States. A total of 2114 individual responses were obtained for this study. As for the eligibility for the study, we placed a screening question at the beginning of the survey and let respondents choose grocery options that they purchased in the last three months. One of the options was "Lettuce or other leafy greens", and only the ones who chose this option were able to participate in the survey. Overall, the sample represents the U.S. population well, except for the slight overrepresentation of the female gender and a higher education level (Table 1). Given the screening question, the former can be an indication that women are more likely to be associated with leafy green consumption [37,38], while the latter might be due to easier access to online surveys [39].

The survey for this study consisted of four sections: (1) leafy green consumption and purchase behavior, (2) leafy green attribute importance, (3) attitude towards IA, and (4) demographics. In the first section, we asked three questions about the frequency of consuming leafy greens and the retail sources from which they buy leafy greens. Regarding consumption frequency, we asked: (1) "How often do you eat leafy greens?", (2) "How often do you prepare your meals at home?", and (3) "How often do you eat leafy green salad at home?". For each of these three frequency questions, respondents chose one of the following five levels: "at least once a day", "3 or more times a week", "1–2 times a week", "2–3 times a month", or "once a month or less frequently". Regarding retail sources, respondents selected options among the following: food subscription or delivery system, farmers markets, gourmet food stores, natural grocery stores, club stores, mass merchandisers, and supermarkets.

Table 1. Statistical summary of the sample socio-demographics and of the U.S. population (%).

		Sample (n = 2114)	**U.S. Population [a]**
Age	18–25 (18–24) [b]	15.61	11.90
	26–35 (25–34) [b]	18.35	17.85
	36–55 (35–54) [b]	31.88	32.43
	56–65 (55–64) [b]	15.37	16.64
	66–80 (65–79) [b]	17.27	16.19
	Over 81 (Over 80) [b]	1.51	4.99
Gender	Female	53.74	50.77
	Male	45.51	49.23
	Prefer to self-describe	0.76	NA
Education	Less than high school degree	2.27	11.47
	High school graduate	23.89	27.58
	Some college or Associate's degree	32.45	30.35
	Bachelor's degree or higher	41.39	30.60
Ethnicity/race [c]	Hispanic	14.66	18.4
	White	73.18	75
	Black or African American	14.05	14.2
	American Indian or Alaska Native	1.28	1.7
	Asian	4.30	6.8
	Native Hawaiian or Pacific Islander	0.85	0.4
	Other or mix	6.34	5.5
Marital status	Married	50.47	47.6
Household size	1 person	19.91	28.3
	2 persons	35.90	34.3
	3 persons	18.83	15.3
	4 or more persons	25.35	22.1
Household income (USD/year)	less than 10,000	6.24	5.8
	10,000–49,999	39.03	32.6
	50,000–99,999	32.54	30.2
	100,000–149,999	14.90	15.7
	150,000–199,999	3.93	7.2
	200,000 or more	3.36	8.5
Living area	Urban area	79.61	80.7
	Rural area	20.39	19.3

[a] U.S. population estimates were obtained from the U.S. Census Bureau's 2019 American Community Survey.
[b] Age brackets used for the U.S. population in parenthesis. [c] Multiple choice question.

In the second section, we asked which leafy green characteristics are important for the respondents when they buy leafy greens. Respondents chose all that applied from the given list: taste, freshness, locally grown, low environmental impact/carbon footprint, food safety, nutrient levels, consistent product quality every time, and price.

In the third section, consumers' attitudes towards IA were elicited. Respondents evaluated IA as an alternative to conventional growing methods: greenhouse (GH) or field farming (FF), assuming consumers are likely to see IA as another category of growing methods, yet comparable to these conventional growing methods. Through eight Likert-scale-type questions, subjects indicated the level of agreement on a scale from one to five (1 = strongly disagree, 2 = somewhat disagree, 3 = neither disagree nor agree, 4 = somewhat agree, 5 = strongly agree) (Table 2). The first six questions were designed to elicit consumers' attitudes towards IA. When designing these attitude questions, we considered findings from the literature [2,4,5,9,14–16,28] and consulted a focus group of industry advisors. Five of these statements referred to the potential benefits of IA, and one asked about the unnatural or artificial aspect of IA. The latter was based on the hypothesis that IA could face rejection by some consumers [28]. The seventh question asked how much survey participants were certain about their knowledge of IA in responding to the preceding questions. Confidence in knowledge is closely related to the strength of attitude formation [40]. Finally, consumer acceptance was defined as the level of willingness to consume IA produce measured by directly asking in the last question whether they would be willing to consume IA produce. Demographic information was collected including age, gender, education level, ethnicity, marital status, household size, household income, area of living place, and zip code of residence.

Table 2. Statements used in survey to elicit attitude towards IA.

Order	Type	Statements
1	Potential assets	Indoor agriculture (IA) makes it possible to grow higher quality leafy greens than field farming and greenhouse.
2		Indoor agriculture (IA) employs less labor than field farming and greenhouse.
3		Indoor agriculture (IA) makes it easier to produce leafy greens locally than field farming and greenhouse.
4		Indoor agriculture (IA) production is less harmful to the environment compared to field farming and greenhouse.
5		Indoor agriculture (IA) will be a mainstream production method in the future.
6	Possible liability	Indoor agriculture (IA) is an artificial and unnatural way of growing crops.
7	Knowledge	I have enough prior knowledge of Indoor agriculture (IA) to feel comfortable about my answers to the last 6 questions.
8	Impact	Given what I know about Indoor agriculture (IA), I am willing to consume leafy greens grown in this type of farm.

3. Methodology Overview

A series of analyses was conducted to identify and describe leafy green consumers' stratification in terms of attitudes towards IA (Figure 1). Firstly, we conducted a principal component analysis (PCA) to identify underlying components explaining the variation in the attitudes towards IA. This also allowed us to understand the loading structure of the components, showing underlying components that drive consumers' attitude towards IA.

Secondly, we conducted a two-step cluster analysis (CA) [41], which was a combination of hierarchical clustering and k-means clustering, using the scores of the principal components obtained from the PCA as the clustering variable to find distinctive clusters with respect to attitudes towards IA. Although we lost some of the information by using PCA scores instead of raw data, the PCA allowed us to extract the most-important information in the attitude data with reduced noise, making clustering more stable and visible, as they are most spread out [42,43].

Thirdly, we compared the likelihood of the willingness to consume IA produce for each cluster to identify the relationship between attitudes towards IA as a production method and acceptance of IA produce. Using the willingness to consume IA produce as an ordinal dependent variable and using cluster memberships obtained from CA as the explanatory variables, we fit an ordered logit model (OLM) to investigate how these clusters would contribute to the likelihood of the willingness to consume IA produce.

Finally, we fit the logit models (LMs) to predict the cluster memberships using individual leafy green consumer's demographic characteristics, leafy green consumption and purchase behavior, and psychographics—self-reported leafy green attribute importance.

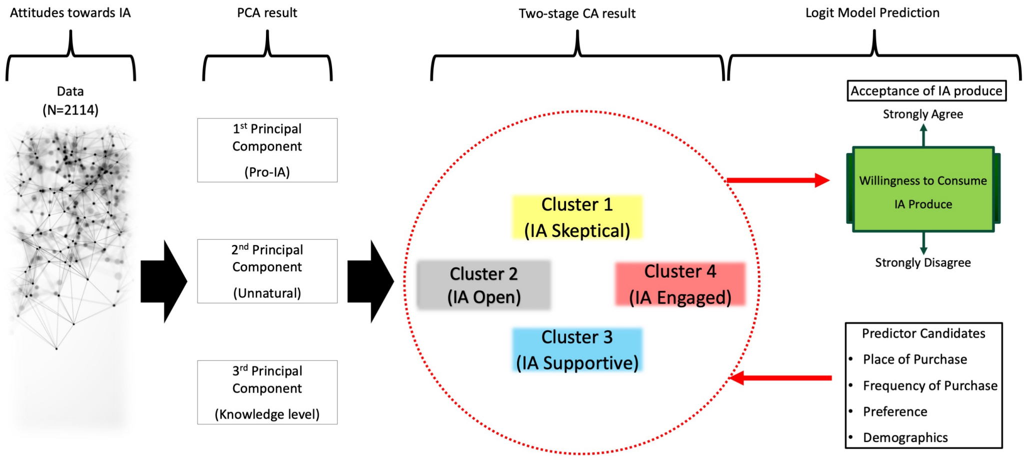

Figure 1. Methodological framework: attitudes towards indoor agriculture (IA) data were analyzed using a principal component analysis (PCA), two-stage cluster analysis (CA), and logit model.

4. Results

4.1. PCA Analysis—Pro-IA, Unnatural, Knowledge Level

The PCA with Kaiser's varimax rotation [44] was performed using responses for the seven Likert-type questions about attitudes towards IA, which included: potential assets of IA; possible liability of IA; and respondent knowledge of IA. The present study reports the results primarily using Pearson correlation matrices for the PCA, but we also tested polychoric correlations for robustness [45]. The difference between using two types of correlation matrix was not significant in our case.

The sample adequacy was satisfied for the PCA. The Kaiser–Meyer–Olkin (KMO) measure of our data was 0.8676, indicating that the attitude variables had much in common to warrant a PCA, and the total variance explained reached 71.16% with the three principal components.

The first component was loaded heavily by the first five variables, which were all about potential benefits of IA, as opposed to the sixth (unnatural or artificial) and seventh (knowledge) variable. The correlations between the first component and the first five variables ranged from 0.43 to 0.49, meaning that the first component was positively correlated with various potential benefits of IA. The loading structure of this component implied that there existed a relatively higher correlation among the five given potential benefits of IA. For this reason, we refer to the first component as "Pro-IA".

The second component was loaded heavily by the "Unnatural/Artificial" variable. This variable was expected to be negatively correlated with the variables about the potential benefits of IA, given the reported literature on consumer rejection of innovative technology in food production. We, therefore, expected that subjects who viewed IA as unnatural would disagree with statements that would imply a positive attitude and, thus, view IA negatively. However, the loading structure of the second component seemed to explain attitude independently given that no significant correlation was observed between the unnaturalness of IA and the positive aspects of IA. We named the second component as "Unnatural/Artificial".

The third component was loaded heavily by the "Confidence in knowledge of IA" variable. Interestingly, this variable was neither correlated with the potential benefits of IA, nor with the "Unnatural/Artificial" variable. Its loading structure implied that confidence in knowledge about IA was not significantly correlated with any other attitude variables. We refer to the third component as "Knowledge level".

4.2. Cluster Analysis—Skeptics, Open, Supportive, Engaged

Using the scores of the three components from the PCA as clustering variables, we performed a CA to group subjects who shared similar attitude towards IA. We applied the two-step procedure as proposed by Mazzocchi [41] for the CA in our study to increase the accuracy and validity of the clustering process. In the first step, the number of clusters and their centroids were determined by hierarchical agglomerative clustering with Ward's method. In the determination of the number of clusters, we considered not only the dissimilarity measure, but also the variation across clusters with respect to the variables of interest. For the cluster stopping rule, we used the Calinski and Harabasz pseudo-F index, which gives guidance for choosing the number of clusters with the more distinct clustering. In the second step, the non-hierarchical K-means clustering method was used to cluster the sample, using the number of clusters and cluster centroids determined from the first step. For the comparison of the mean scores of the attitude variables by clusters, we conducted the Kruskal–Wallis test across four clusters. We also conducted single-sample t-tests for each cluster and variable. The null hypothesis of the single sample t-tests was that the population mean was 3. In other words, we tested whether the average consumer in each cluster was neutral in terms of the given attitude.

We discovered four distinct clusters of consumers in the sample (Table 3). As the different superscripts showed, we can reject the null hypothesis that the four clusters were from the same population at the 0.5% significance level for each attitude variable.

Table 3. Consumer responses to attitude variables by four clusters.

Variables Observations (%)	**IA Skeptics 651 (30.8)**	**IA Open 529 (25)**	**IA Supportive 628 (29.7)**	**IA Engaged 306 (14.5)**
Higher Quality ‡	2.710 *** a (0.792)	3.214 *** b (0.687)	3.828 *** c (0.753)	4.670 *** d (0.572)
Less Labor ‡	2.957 a (0.801)	3.473 *** b (0.663)	3.815 *** c (0.724)	4.739 *** d (0.448)
Local Easier ‡	2.839 *** a (0.746)	3.452 *** b (0.678)	3.997 *** c (0.687)	4.703 *** d (0.518)
Better Environment ‡	2.730 *** a (0.847)	3.189 *** b (0.692)	3.895 *** c (0.713)	4.663 *** d (0.590)
Mainstream Future ‡	2.954 a (0.836)	3.543 *** b (0.735)	4.150 *** c (0.656)	4.712 *** d (0.514)
Unnatural/Artificial ‡	3.296 *** a (0.967)	3.034 b (0.902)	2.490 *** c (1.097)	4.559 *** d (0.705)
Confidence in Knowledge of IA ‡	3.401 *** a (0.860)	2.066 *** b (0.719)	3.978 *** c (0.703)	4.585 *** d (0.693)

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$. ‡ Means from the Likert scale running from 1 (strongly disagree) to 5 (strongly agree), with 3 being neutral. a,b,c,d Different superscripts show the significant difference from the Kruskal–Wallis test ($p < 0.01$).

The first leafy green consumer cluster accounted for 30.8% of the sample. The mean scores of the first five attitude variables, potential benefits of IA, for this cluster were all less than 3, which was the lowest compared to other clusters. This means that consumers in the first cluster, on average, were more likely to lean towards disagreeing with the potential benefits of IA than consumers in any other clusters. On the other hand, the mean of the "Unnatural/Artificial" variable was greater than 3, meaning that consumers in the first cluster, on average, were more likely to believe that IA is an unnatural or artificial way of growing crops. The mean of the "Confidence in knowledge of IA" variable was greater than 3 for this cluster, suggesting that, on average, they believed they had enough knowledge of IA to confidently answer all the attitude questions. The mean score of this variable, however, was rather close to 3, neutral, compared to the clusters with a strong confidence level in knowledge of IA. Given this combination of attitudes, we refer to the first cluster as "IA Skeptics"—leaning negatively toward positive IA attributes, leaning positively toward unnatural, and having some knowledge of IA.

The second leafy green consumer cluster accounted for 25% of the sample. Unlike the "IA Skeptics", consumers in this cluster, on average, were positioned towards agreeing with the potential benefits of IA, as the mean scores of the first five attitude variables were slightly greater than 3. The mean score of the "Unnatural/Artificial" variable was not statistically different from 3, that is the null hypothesis cannot be rejected at acceptable significance levels. The most-distinctive feature of this cluster was that the mean score of the "Confidence in knowledge of IA" variable was 2, the lowest among the other clusters. In other words, the average consumer in this cluster thought that they did not have enough prior knowledge of IA to confidently answer attitude questions. This is consistent with the fact that their answers to attitude questions were positive, but relatively closer to 3 (neither agree nor disagree) compared to the consumers in other clusters. We refer to this cluster as "IA Open" considering that the mean scores of the attitude variables leaned towards positive. In other words, they had weak positive attitudes, suggesting that they were open to choosing IA produce, but likely needed additional confirming information to achieve acceptance.

The third leafy green consumer cluster accounted for 29.7% of the sample, which was almost the same percentage as "IA Skeptics". The average consumer in this cluster agreed with the potential benefits of IA, disagreed with the statement about the unnaturalness of IA, and had prior knowledge of IA. Overall, consumers in this cluster clearly had positive attitudes towards IA with a fair amount of confidence in the knowledge of IA. For this reason, we refer to the third cluster as "IA Supportive".

The fourth leafy green consumer cluster accounted for 14.5% of the sample, the smallest among the four clusters. The average consumer in this cluster strongly believed in the potential benefits of IA as presented by the highest mean scores of the first five attitude variables among the four clusters. Interestingly, the average consumer in this cluster also strongly agreed with the statement saying that IA is an unnatural or artificial way of growing crops. In other words, they found the novel technology to be a positive attribute rather than a negative one. Perhaps this is true because they are technology lovers in other parts of their lives. Additional research is needed to study this hypothesis. Based on a very strong confidence in their prior knowledge of IA and seeing IA as an artificial production system, they believed in the potential benefits of IA more than any other consumers in the sample. Hence, we named the fourth cluster as "IA Engaged".

In Figure 2, we present the score plot on a three-dimensional space of principal components showing how clusters were clearly and distinctly distributed in relation to the three principal components.

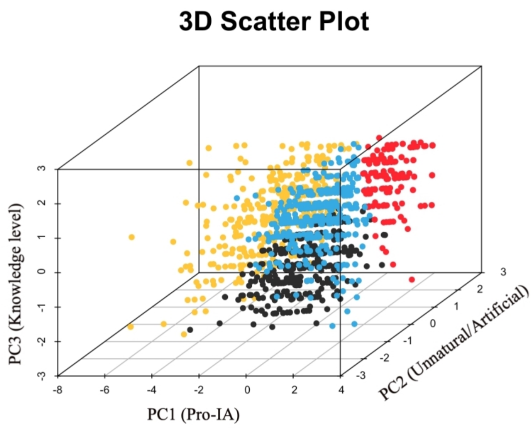

Figure 2. Scatter plot of the scores of the principal components of individual consumers on the 3-dimensional space of the principal components (PC). Yellow, black, blue, and red represent Skeptics, Open, Supportive, and Engaged, respectively.

4.3. Acceptance of IA Produce by Four Clusters

Consumer acceptance of IA as a production system was elicited at the end of the attitude questions by directly asking: "Given what I know about Indoor Agriculture (IA), I am willing to consume leafy greens grown in this type of farm." Using these answers, as an ordinal dependent variable, we fit an ordered logit model (OLM) to investigate the effect of the four cluster memberships—"IA Skeptics", "IA Open", "IA Supportive", and "IA Engaged"—on the likelihood of the willingness to consume IA produce. See Appendix A and Table A1 for the full OLM specification and estimated coefficients.

We set "IA Skeptics" as the benchmark group, assuming these respondents were more likely to reject consuming IA produce given their negative view of the positive aspects of IA. The estimated OLM coefficients for the cluster memberships were all positive, indicating that respondents in the clusters "IA Open", "IA Supportive", and "IA Engaged" were more likely to consume IA produce than those in the benchmark group, "IA Skeptics". Since statistically significant estimates for the cut-off values were obtained, which makes the categories of the ordered dependent variables separable, we did not collapse the categories. We further investigated the average marginal effects to see which cluster had the highest acceptance for IA produce on average. The five categories in the ordinal dependent variable (1 = strongly disagree to 5 = strongly agree) formed five sets of average marginal effects for each of three cluster membership that was included in the OLM (Table 4).

Table 4. Average marginal effect of cluster membership on the likelihood of the acceptance of IA produce, obtained after estimating the OLM. See the OLM results table in Appendix A Table A1.

Level of Willingness to Consume IA Produce	IA Open	IA Supportive	IA Engaged
Strongly disagree	−0.024 ***	−0.068 ***	−0.101 ***
	(0.004)	(0.009)	(0.013)
Somewhat disagree	−0.040 ***	−0.111 ***	−0.164 ***
	(0.006)	(0.010)	(0.015)
Neither agree nor disagree	−0.086 ***	−0.242 ***	−0.356 ***
	(0.010)	(0.011)	(0.018)
Somewhat agree	0.023 ***	0.064 ***	0.093 ***
	(0.003)	(0.009)	(0.016)
Strongly agree	0.128 ***	0.358 ***	0.527 ***
	(0.016)	(0.017)	(0.016)

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$. Cluster membership of "IA Skeptics" is omitted for benchmark purposes.

Overall, the willingness to consume IA produce was the highest for "IA Engaged", followed by "IA Supportive" and "IA Open", respectively. For each of the five categories of the ordinal dependent variables, the average marginal effect was the greatest in absolute value for "IA Engaged" and smallest in absolute value for "IA Open". Take "Strongly agree" for example: respondents in "IA Engaged" were 52.7% more likely to be in the "Strongly agree" category of the dependent variable, willingness to consume IA produce, than those in the "IA Skeptics" group. The same average marginal effect for "IA Supportive" and "IA Open" was 35.8% and 12.8%, respectively. Similarly, respondents in "IA Engaged" were 10.1% less likely to answer "Strongly disagree" when asked about the willingness to consume IA produce, compared to "IA Skeptics". The same average marginal effect for "IA Supportive" and "IA Open" was 6.8% and 2.4%, respectively.

4.4. Predicting Cluster Memberships

In this last part of the analysis, we expanded the description of the clusters by allocating demographic and behavior data to each cluster. To that end, we fit the logit models (LMs) to investigate the effect of the four different sets of explanatory variables in predicting all four cluster memberships: (1) demographic characteristics; (2) frequency of consuming leafy greens; (3) retail source for purchasing leafy greens; and (4) self-reported leafy green attribute importance. The variables were used as a binary dependent variable for each of the four cluster memberships, resulting in 16 LMs. See Appendix B for a detailed description of the applied LM specification.

4.4.1. Demographics of Four Clusters

Some demographic variables were informative in predicting the cluster membership (Table 5). The positive sign of the coefficients with higher value indicated that the explanatory variable was more likely to be in that cluster. Among the four generation categories, Generation X was omitted for benchmark purposes. Compared to Generation X, Generation Z was more likely to be in "IA Skeptics" and less likely to be in "IA Supportive". On the other hand, Baby Boomers were less likely to be "IA Engaged", but more likely to be in "IA Open" or "IA Supportive". This result implied the relationship between age and attitude towards IA represented by the four clusters was less likely to be a simple linear relationship.

The coefficient of the male variable was significant in the second and fourth models, implying that males were less likely to be "IA Open", but more likely to be "IA Engaged'. This result was consistent with previous literature about gender differences in the acceptance of novel food technologies such as genetically modified foods [46].

Education level was found to be a significant explanator when it came to predicting cluster membership. We set consumers who chose "High school graduate (high school diploma or equivalent including general educational development test)" for their education level as the baseline. Overall, there was a positive relationship between education level and acceptance of IA. Consumers who reported an education level less than high school graduate were less likely to be in "IA Engaged" than baseline consumers. Consumers with at least some college education were less likely to be in "IA Skeptics". Consumers with a post-graduate level of education—Master's, Doctoral, or professional degree—were less likely to be in "IA Skeptics" and more likely to be in "IA Engaged". This result was consistent with the literature that education can reduce "food neophobia" [47].

Living area in terms of urban, sub-urban, and rural area was also informative to predict cluster membership. Consumers living in urban areas were less likely to be in "IA Skeptics", but more likely to be in "IA Engaged" compared to baseline consumers who lived in rural areas. Consumers living in sub-urban areas were less likely to be in "IA Skeptics", but more likely to be in "IA Open".

Table 5. Average marginal effect of demographic characteristics on the likelihood of being in clusters.

Variables	(1) Skeptics	(2) Open	(3) Supportive	(4) Engaged
Generation				
Generation Z (18–25) [a]	0.134 ***	−0.023	−0.094 ***	−0.021
	(0.031)	(0.032)	(0.036)	(0.022)
Millennials (26–40) [a]	0.002	−0.020	0.006	0.021
	(0.028)	(0.028)	(0.028)	(0.017)
Baby Boomers (56 and over) [a]	−0.043	0.105 ***	0.060 **	− 0.172 ***
	(0.027)	(0.025)	(0.026)	(0.024)
Gender				
Male	−0.023	−0.114 ***	0.029	0.103 ***
	(0.020)	(0.019)	(0.020)	(0.015)
Education level				
Less than high school degree	0.056	0.077	−0.014	−0.219 **
	(0.062)	(0.064)	(0.074)	(0.104)
Some college, but no degree	−0.059 **	0.054 **	0.029	−0.015
	(0.027)	(0.027)	(0.029)	(0.023)
Associate's degree in college (2-year)	−0.111 ***	0.072 **	0.017	0.034
	(0.037)	(0.034)	(0.037)	(0.028)
Bachelor's degree in college (4-year)	−0.100 ***	0.068 **	0.038	0.004
	(0.030)	(0.028)	(0.030)	(0.023)
Graduate or professional degree	−0.127 ***	0.036	−0.030	0.081 ***
	(0.034)	(0.033)	(0.035)	(0.022)
Annual household income				
Second quarter (less than USD 30,000/year)	−0.077 ***	0.012	0.091 ***	−0.022
	(0.025)	(0.025)	(0.027)	(0.021)
Third quarter (USD 30,000–USD 60,000/year)	−0.066 **	−0.009	0.089 ***	−0.005
	(0.029)	(0.028)	(0.030)	(0.023)
Fourth quarter (more than USD 60,000/year)	−0.089 ***	−0.051 *	0.051	0.056 **
	(0.032)	(0.031)	(0.033)	(0.022)
Living area				
Urban area	−0.071 **	0.008	−0.025	0.061 ***
	(0.028)	(0.028)	(0.029)	(0.022)
Sub-urban area	−0.061 **	0.063 ***	−0.005	0.008
	(0.025)	(0.024)	(0.026)	(0.022)
Observations	2114	2114	2114	2114

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables in Models (1), (2), (3), and (4) are cluster membership for IA Skeptics, IA Open, IA Supportive, and IA Engaged, respectively. Generation X (41–55), female, high school degree, first income quarter, and rural area were omitted for benchmark purposes. [a] Age in 2021.

4.4.2. Leafy Green Consumption and Purchase Behavior of Four Clusters

Regarding consumers' self-reported behavior, we asked about the frequency of consuming leafy greens and where they buy leafy greens. Overall, self-reported leafy green consumption behavior and purchase source were informative in predicting the cluster memberships (Tables 6 and 7).

Table 6. Average marginal effect of self-reported leafy green consumption behavior on the likelihood of being in clusters.

Variables	(1) Skeptics	(2) Open	(3) Supportive	(4) Engaged
How often do you eat leafy greens? [a]				
2–3 times a month	0.014	0.023	−0.043	0.012
	(0.089)	(0.088)	(0.099)	(0.078)
1–2 times a week	0.027	−0.015	0.017	−0.027
	(0.084)	(0.082)	(0.095)	(0.072)
3 or more times a week	−0.006	0.014	−0.007	0.010
	(0.084)	(0.082)	(0.094)	(0.071)
At least once a day	−0.059	−0.021	0.017	0.066
	(0.086)	(0.084)	(0.097)	(0.074)
How often do you prepare your meals at home? [a]				
2–3 times a month	0.049	0.008	−0.098	0.051
	(0.118)	(0.093)	(0.096)	(0.096)
1–2 times a week	−0.073	0.017	0.009	0.072
	(0.099)	(0.077)	(0.087)	(0.080)
3 or more times a week	−0.162 *	0.036	0.087	0.054
	(0.095)	(0.074)	(0.083)	(0.075)
At least once a day	−0.145	0.058	0.086	0.014
	(0.094)	(0.073)	(0.083)	(0.074)
How often do you eat leafy green salad at home? [a]				
2–3 times a month	−0.109	0.043	0.054	0.022
	(0.076)	(0.067)	(0.067)	(0.040)
1–2 times a week	−0.172 **	0.094	0.079	0.011
	(0.073)	(0.064)	(0.063)	(0.036)
3 or more times a week	−0.171 **	−0.015	0.106 *	0.094 **
	(0.073)	(0.063)	(0.063)	(0.038)
At least once a day	−0.167 **	−0.057	0.070	0.162 ***
	(0.077)	(0.065)	(0.067)	(0.044)
Observations	2114	2114	2114	2114

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables in Model (1), (2), (3), and (4) are cluster membership for IA Skeptics, IA Open, IA Supportive, and IA Engaged, respectively. [a] Frequency level "once a month or less" was omitted for benchmark purposes.

The frequency of consuming leafy greens in general or the frequency of preparing meals at home were not statistically significant in predicting cluster membership. On the other hand, the frequency of eating leafy green salad at home was useful to predict cluster membership. On average, consumers who ate leafy green salad at home at least once a day were 16.2% more likely to be "IA Engaged" than the consumers who ate leafy green salad at home once a month or less. Furthermore, consumers who ate leafy green salad at least once a day were less likely to be "IA Skeptics" than the consumers who ate leafy green salad at home once a month or less. The result implied a positive relationship between the frequency of eating leafy green salad at home and the acceptance of IA produce, which is likely a positive implication for IA stakeholders.

Leafy green consumers who bought leafy greens by food subscription or delivery system were more likely to be "IA Engaged",. Consumers who bought leafy greens from gourmet food stores, natural grocery stores, club stores, and mass merchandisers were also likely to be "IA Engaged", but less likely than consumers using food subscriptions or delivery systems. Interestingly, supermarket users were less likely to be "IA Engaged", but more likely to be "IA Supportive". Farmers market users were more likely to be "IA Supportive". This result informs marketing strategy design regarding which retail outlet to target as different segments of IA consumers could be found patronizing different types of leafy green retail outlets.

Table 7. Average marginal effect of self-reported leafy green purchase source on the likelihood of being in clusters.

Variables	(1) Skeptics	(2) Open	(3) Supportive	(4) Engaged
Food subscription or delivery system	−0.111 ***	−0.104 ***	−0.203 ***	0.167 ***
	(0.037)	(0.039)	(0.039)	(0.015)
Farmers markets	0.009	−0.074 ***	0.061 ***	0.002
	(0.022)	(0.021)	(0.022)	(0.015)
Gourmet food stores	−0.043	−0.090 **	−0.009	0.047 ***
	(0.036)	(0.040)	(0.036)	(0.017)
Natural grocery stores	−0.016	−0.077 ***	−0.006	0.081 ***
	(0.023)	(0.023)	(0.023)	(0.014)
Club stores	−0.042	−0.038	−0.004	0.057 ***
	(0.027)	(0.025)	(0.026)	(0.015)
Mass merchandisers	−0.106 ***	0.007	0.032	0.045 ***
	(0.023)	(0.021)	(0.022)	(0.014)
Supermarkets	−0.063 ***	0.043 *	0.066 ***	−0.060 ***
	(0.023)	(0.024)	(0.025)	(0.014)
Observations	2114	2114	2114	2114

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables in Models (1), (2), (3), and (4) are cluster membership for IA Skeptics, IA Open, IA Supportive, and IA Engaged, respectively.

4.4.3. Self-Reported Leafy Green Attribute Importance of Four Clusters

In one section of the survey, consumers were able to show their opinion about the importance of leafy green attributes when buying leafy greens. Consumers were asked to choose all characteristics of leafy greens that were important to them among the following nine items: taste, freshness, locally grown, low environmental impact/carbon footprint, food safety, nutritional value, consistent product quality every time, price, and other. The choice among these attributes can reflect consumers' interests or opinions. These choices were informative in predicting the cluster memberships (Table 8).

Whether a consumer considered environmental impact to be important seemed to be another predictor to identify "IA Engaged". Consumers who selected low environmental impact or carbon footprint as an important attribute when buying leafy greens were more likely to be "IA Engaged". This was consistent with the result that "IA Engaged" consumers tended to strongly agree with the statement that IA is less harmful to the environment compared to other agricultural production methods (Table 3). Whether leafy greens are locally grown was also important for "IA Engaged" consumers. This finding was consistent with previous reports that consumers often believe local foods are environmentally friendly [48]. These results suggest that the IA industry would attract "IA Engaged" consumers as a locally grown and environmentally friendly agricultural production method with a lower carbon footprint. IA can potentially reduce the environmental impact by circulating resources and reducing food mileage; however, it also requires a great deal of energy to operate the IA farm [5]. Lowering the environmental impact of IA would likely be helpful to not only enhance environmental sustainability, but also improve the profitability of IA farms.

Table 8. Average marginal effect of self-reported leafy green attribute importance on the likelihood of being in clusters.

Variables	**(1) Skeptics**	**(2) Open**	**(3) Supportive**	**(4) Engaged**
Taste	−0.015	−0.031	−0.021	0.083 ***
	(0.022)	(0.020)	(0.022)	(0.019)
Freshness	−0.051 *	−0.025	0.208 ***	−0.085 ***
	(0.030)	(0.030)	(0.039)	(0.021)
Locally grown	−0.032	−0.068 ***	−0.005	0.090 ***
	(0.022)	(0.022)	(0.022)	(0.015)
Low environmental impact/carbon footprint	−0.060 **	−0.098 ***	−0.024	0.114 ***
	(0.030)	(0.029)	(0.028)	(0.017)
Food safety	−0.035	−0.000	−0.008	0.045 ***
	(0.021)	(0.020)	(0.021)	(0.016)
Nutritional value	−0.012	−0.037 *	0.027	0.026
	(0.022)	(0.021)	(0.022)	(0.017)
Consistent product quality every time	−0.102 ***	0.065 ***	0.056 ***	−0.029 *
	(0.021)	(0.020)	(0.021)	(0.017)
Price	−0.022	0.066 ***	−0.030	−0.026 *
	(0.020)	(0.019)	(0.020)	(0.015)
Observations	2114	2114	2114	2114

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables in Models (1), (2), (3), and (4) are cluster membership for IA Skeptics, IA Open, IA Supportive, and IA Engaged, respectively.

5. Discussion

This study revealed that the emerging IA industry has a significant market opportunity with leafy green consumers given their broad willingness to consume products from this advanced technology. While a strong heterogeneity among consumers was identified, this study also revealed a promising segment, namely the IA Engaged. Marketing strategies must target this group by emphasizing the technology used to produce high- and consistent-quality produce through multiple outlets. This segment is, however, only 14.5% of the market. To broaden the market, the IA Supportive (29.7%) segment needs to be targeted. Various niche strategies are likely to be successful here based on high-quality, high-price, and high-margin positioning. The emphasis can again be on high- and consistent-quality produce, but perhaps slightly less emphasis on the IA technology itself. Together, the IA Engaged and IA Supportive represented 45% of the market, which provides a substantial revenue and profit opportunity for the industry.

The other two segments were more difficult to target. The IA Open (25%) were the most price sensitive and least IA knowledgeable. Increasing their knowledge would likely result in positive consumption growth, as long as IA prices are in line with other high-quality produce on the market. The skeptics (30.8%) would be the hardest to reach. More positive knowledge about IA would likely be helpful to overcome their concerns about IA's benefits.

In general, the industry needs to pursue marketing strategies that further increase consumer awareness and acceptance of its produce to successfully achieve economic sustainability. This starts from a promising foundation of three market segments (75% of consumers) being strongly or leaning towards acceptance. The remaining 25% are skeptical, but do not reject its technology. Other novel agricultural systems have emerged from a less positive beginning.

Although beyond the scope of this paper, it is also important to understand how leafy green retailers view IA produce and its advanced technology to guide the IA industry to the right place. Large food retailers have actively played a significant role in shaping consumer food choice, for example by providing additional options to the consumers or conducting creative marketing strategies [49]. Food retailer preference will add complexities to IA growers' strategies regarding how to achieve sustainable profits. Future research on retailer attitude towards IA produce would bring more information on the optimal business strategy for the IA industry to grow.

6. Conclusions

Indoor agriculture (IA) has the potential to become a major contributor to the future of agricultural production given its ability to significantly reduce resource use while optimizing plant growth and quality through extensive control of the environmental variables. However, empirical studies on the economics and consumer acceptance of IA are nascent in the literature. We contribute to the literature by providing evidence of consumer attitude heterogeneity using principal component analysis (PCA) and a two-step cluster analysis (CA) applied to a sample representing the general U.S. population. As a steppingstone for future analysis on the economic sustainability of IA, we investigated consumer attitudes towards IA, confidence in the knowledge of IA, and the willingness to consume IA produce by using a unique dataset of 2,114 survey responses representing U.S. leafy green consumers. The segmentation of these consumers can allow stakeholders to define market opportunities for IA produce.

We found evidence that a majority of consumers are ready to accept IA produce, but with significant variability. Through the CA, we identified four clusters of leafy green consumers who shared similar attitudes towards IA within each cluster. We called the first cluster "IA Skeptics" (30.8% of respondents), because the average consumer in this cluster had a relatively moderate level of confidence in the knowledge of IA and leaned slightly towards disagreeing with the potential benefits of IA. The second cluster was named "IA Open" (25%), because they leaned towards agreeing with the potential benefits. Yet, these consumers, on average, had the least confidence in their knowledge of IA among the four clusters. The third and fourth clusters both had strong positive attitudes toward IA's benefits. We called the third cluster "IA Supportive" (29.7%) because these consumers had solid confidence in their knowledge of IA and strong acceptance. A distinctive feature of this cluster vs. the fourth was that they did not think IA was an unnatural way of growing crops. The fourth cluster was referred to as "IA Engaged" (14.5%), because consumers in this cluster showed not only the strongest belief in the potential benefits of IA, but also the highest confidence in the knowledge of IA. Unlike the third cluster, this cluster perceived IA systems to be artificial/unnatural, but did not indicate this as a negative aspect. We hypothesized that the reason for their strong acceptance was rooted in their strong confidence in the knowledge of IA and strong acceptance of the high technology found in IA. Given other demographic characteristics, these consumers are generally likely to be technology engaged.

It is worth noticing that no clear knowledgeable opposer IA cluster was identified from the CA, a cluster we might have named "knowledgeable rejectors". A priori, we hypothesized that such a cluster could exist because of consumer opposition to other novel high technology food processes. Such a consumer cluster could be described as strongly disagreeing with the benefits of IA and strongly agreeing with the unnatural/artificial attribute of IA produce due to adverse attitudes towards IA technology. Although we found a consumer cluster that could be called "IA Skeptics", 36.7% of them were willing to consume IA produce (Figure 3). The expectation that the perception of unnaturalness or artificialness would move consumers strongly away from IA was not confirmed. This finding is consistent with the food technology literature [20]. The absence of a "knowledgeable rejectors" cluster might be because IA is still not a familiar concept to U.S. consumers. Several previous studies and our results indicated the existence of nontrivial shares of consumers who are not confident in their knowledge of IA. The literature on the acceptance of novel food technology reports evidence that knowledge or confidence can enhance the likelihood of acceptance [21–23], though the relationship between knowledge and acceptance must be disentangled carefully [50].

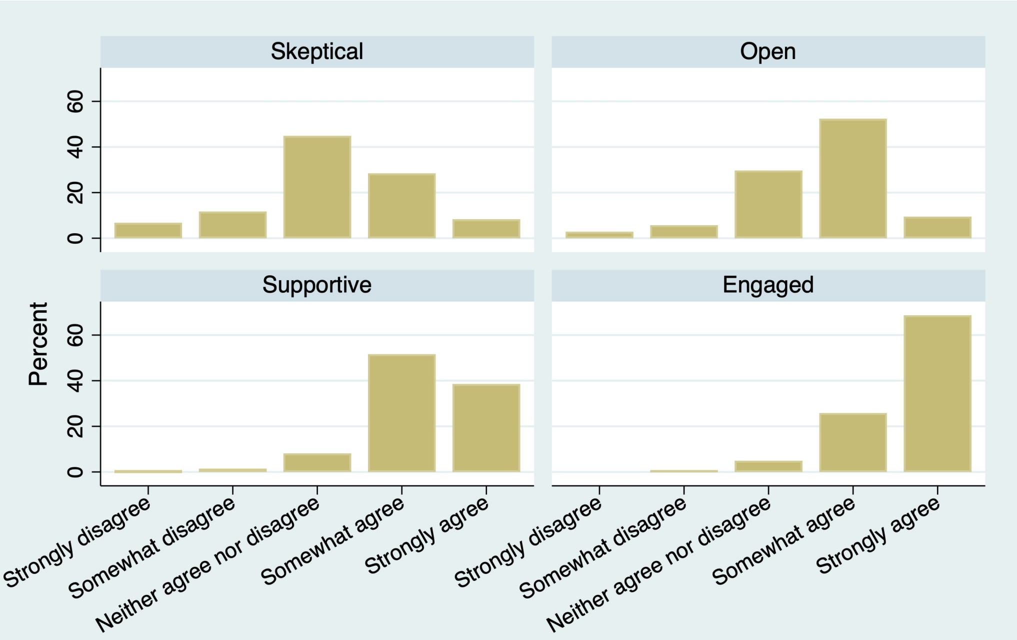

Figure 3. Willingness to consume IA produce by U.S. leafy green consumer cluster.

The share of each cluster showed the presence of significant attitude heterogeneity in current U.S. leafy green consumers. This heterogeneity seems to be related to some demographic characteristics, which has been reported similarly in other food technology acceptance studies [51–53]. Among the demographic information we collected, gender, education level, and living area were found to be significant explanators. Leafy green consumption behavior was informative in describing where and how often members of these clusters shop for leafy greens. Consumers who more frequently ate salad at home were more likely to be in the "IA Engaged" cluster. Consumers who thought taste, locally grown, low environmental impact, and food safety were important characteristics of leafy greens when buying leafy greens were also more likely to be in the "IA Engaged" cluster.

The market opportunities identified by this study were also discussed. Overall, we suggest that the industry should pursue marketing strategies that further increase consumer awareness and acceptance of IA produce to successfully achieve economic sustainability.

Although our study provided evidence for preference heterogeneity among U.S. consumer by identifying consumer segments, these were associated with consumer attitudes towards IA and did not readily relate to the estimates of the willingness to pay. Future study is necessary to specifically estimate consumer willingness to pay and investigate the relationship between willingness to pay and these results of consumers' attitudes towards IA.

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Appendix A

OLM Specification

The theoretical framework was based on Lancaster's consumer theory [54]. According to Lancaster's consumer theory, consumers derive utility from the attributes of a product instead of the product itself. In this analysis, we considered that the production method of leafy greens is one of the leafy green attributes. Following Lancaster's approach, we framed the leafy green consumer's choice problem as the choice between consuming IA produce (I) or not (N). Given that every respondent who participated in this survey stated being a lettuce or leafy green consumer, the alternative choice of not consuming IA produce could be understood as the choice of consuming a leafy green grown by greenhouse or field farming. However, our data were restricted to consumer statements between strongly disagreeing and strongly agreeing that they were willing to consume leafy greens produced in an IA system, exclusively. We proceeded using these response choices as an indication of consumer willingness to consume and adopted the assumption prescribed by Lancaster's theory that consumers will make a choice in a way that maximizes their utility, which in this case resulted from their willingness to consume IA produce. We formulated the utility representation of consumer i choosing leafy greens with attribute $j(j = I, N)$ as follows:

$$U_{ji} = V_{ji} + \epsilon_{ji} \tag{A1}$$

where V_{ji} is the deterministic portion and ϵ_{ji} is the random component of the utility.

We define Z_i as the difference in utilities between choosing and not choosing to consume IA produce as follows:

$$Z_i = (V_{Ii} + \epsilon_{Ii}) - (V_{Ni} + \epsilon_{Ni}) = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni}) \tag{A2}$$

Consumer i's choice ordering, which we denote as Y_i, depends on Z_i because the difference in utility represents the additional utility gain from choosing one against the other. Y_i is the observed choice ordering, respondent i's willingness to consume IA produce measured by a five-point scale of Likert-type question. Therefore, Y_i becomes the degree of consumer acceptance of IA produce. In order to formulate the relationship between the observed choice ordering, Y_i and Z_i, we denote μ_1, μ_2, μ_3, and μ_4 as the cut-off points that are unknown to the researcher. In this approach, consumer i will strongly reject consuming IA produce ($Y_i = 1$) if $Z_i \leq \mu_1$, somewhat reject consuming IA produce ($Y_i = 2$) if $\mu_1 < Z_i \leq \mu_2$, neither reject nor accept consuming ($Y_i = 3$) if $\mu_2 < Z_i \leq \mu_3$, somewhat accept consuming IA produce ($Y_i = 4$) if $\mu_3 < Z_i \leq \mu_4$, and strongly accept consuming IA produce ($Y_i = 5$) if $Z_i > \mu_4$. Thus, we define Y_i as follows:

$$Y_i = \begin{cases} 1 & \text{if } Z_i \leq \mu_1 \\ 2 & \text{if } \mu_1 < Z_i \leq \mu_2 \\ 3 & \text{if } \mu_2 < Z_i \leq \mu_3 \\ 4 & \text{if } \mu_3 < Z_i \leq \mu_4 \\ 5 & \text{if } Z_i > \mu_4 \end{cases} \tag{A3}$$

By assuming that $(\epsilon_{Ii} - \epsilon_{Ni})$ follows the logistic distribution, the probability that consumer i will choose, for example, 1 (i.e., consumer i strongly rejects consuming IA produce), can be expressed as follows:

$$P_{i1} = P(Y_i = 1) = P[Z_i = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni}) \leq \mu_1] = F(\mu_1 - (V_{Ii} - V_{Ni})) \tag{A4}$$

where $F(z) = \frac{e^z}{1+e^z}$, which is the logistic CDF. To complete the ordered logit model, we can express the rest of the probabilities in the same way as follows:

$$\begin{aligned} P(Y_i = 2) &= P[\mu_1 < Z_i = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni}) \leq \mu_2] \\ &= F(\mu_2 - (V_{Ii} - V_{Ni})) - F(\mu_1 - (V_{Ii} - V_{Ni})) \\ P(Y_i = 3) &= P[\mu_2 < Z_i = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni}) \leq \mu_3] \\ &= F(\mu_3 - (V_{Ii} - V_{Ni})) - F(\mu_2 - (V_{Ii} - V_{Ni})) \\ P(Y_i = 4) &= P[\mu_3 < Z_i = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni}) \leq \mu_4] \\ &= F(\mu_4 - (V_{Ii} - V_{Ni})) - F(\mu_3 - (V_{Ii} - V_{Ni})) \\ P(Y_i = 5) &= P[\mu_4 < Z_i = (V_{Ii} - V_{Ni}) + (\epsilon_{Ii} - \epsilon_{Ni})] \\ &= 1 - F(\mu_4 - (V_{Ii} - V_{Ni})) \end{aligned} \tag{A5}$$

Since the interest of the present analysis was to compare the effect of cluster membership on the likelihood of the acceptance of IA produce, Z_i is specified as a function of the cluster membership and random component as follows:

$$Z_i = \beta' x_i + v_i = \beta_1 Cluster2_i + \beta_2 Cluster3_i + \beta_3 Cluster4_i + v_i \tag{A6}$$

where x_i = $(Cluster2_i, Cluster3_i, Cluster4_i)$, β = $(\beta_1, \beta_2, \beta_3)$, and v_i is a stochastic error term. $Cluster2_i$, $Cluster3_i$, and $Cluster4_i$ are the indicator variables for cluster membership of the second, third, and fourth cluster, respectively. Cluster membership of the first cluster is taken as the benchmark category, hence omitted in the model. Indicator variables for the cluster membership take a value of 1 if the respondent is in the cluster and 0 otherwise. For example, if the i-th respondent was classified into the fourth cluster from the CA, then $Cluster2_i = 0$, $Cluster3_i = 0$, and $Cluster4_i = 1$. β is the vector of parameters to be estimated.

The estimation of the parameter was performed by maximum likelihood estimation using the software package STATA 15 (StataCorp LLC, College Station, TX, USA). The log likelihood function is as follows:

$$logL(\mu_k, \beta) = \Sigma_{i=1}^{2114} \Sigma_{k=1}^{5} m_{ik} log[F(\mu_k - \beta' x_i) - F(\mu_{k-1} - \beta' x_i)] \tag{A7}$$

where m is defined as an index of Y_i belonging to the group of k options. In other words, $m_{ik} = 1$ if $Y_i = k$ and 0 otherwise. Maximization can be performed with the following two constraints for the parameters in the log likelihood function: $\mu_0 = -\infty$, $\mu_5 = +\infty$.

Table A1. Estimated parameters in the OLM.

VARIABLES	Coeff. (SD)
Cluster membership	
IA Skeptics ‡	- -
Open	0.890 *** (0.111)
Supportive	2.497 *** (0.121)
Engaged	3.669 *** (0.160)
Threshold parameters	
μ_1	−2.666 *** (0.137)
μ_2	−1.486 *** (0.091)
μ_3	0.480 *** (0.078)
μ_4	2.911 *** (0.106)
Observations	2114
Pseudo R-squared	0.146

Standard errors in parentheses. The *t*-test significance level is represented by asterisks: *** $p < 0.01$. μ_1, μ_2, μ_3, and μ_4 are the estimated cut-off points. ‡: Cluster membership of "IA Skeptics" is omitted for benchmark purposes.

Appendix B

LM Specification

To denote the binary dependent variable, we define c_{ij} as the indicator variable, which is 1 if the *i*-th respondent is in the *j*-th cluster and 0 otherwise. We omitted subscript *j* because it is determined from the CA, thus given in this specification.

Given *j*, c_i is viewed as a realization of a random variable C_i that takes a value of 1 with a probability of π_i and 0 with a probability of $1 - \pi_i$. Then,

$$P(C_i = c_i) = \pi_i^{c_i}(1 - \pi_i)^{1-c_i} \quad for \quad c_i \in \{0, 1\} \tag{A8}$$

which is a Bernoulli distribution.

We define the logit by assuming a linear relationship between the logit and the predictor variables as follows:

$$log\frac{\pi_i}{1 - \pi_i} = \beta' x_i \tag{A9}$$

Rearranging the terms with respect to π_i, which would be included in the likelihood function to maximize, yields:

$$\pi_i = \frac{exp(\beta' x_i)}{1 + exp(\beta' x_i} \tag{A10}$$

The four sets of explanatory variables used as candidate predictors are as follows:

1. $\beta' x_i = \beta_0 + \beta_1 GenZ_i + \beta_2 Millennials_i + \beta_3 Boomers_i + \beta_4 Male_i$
 $+ \beta_5 edulev1_i + \beta_6 edulev3_i + \beta_7 edulev4_i + \beta_8 edulev5_i + \beta_9 edulev6_i$
 $+ \beta_{10} incquar2_i + \beta_{11} incquar3_i + \beta_{12} incquar4_i + \beta_{13} urban_i + \beta_{14} suburban_i$
2. $\beta' x_i = \beta_0 + \beta_1 often1_i + \beta_2 often2_i + \beta_3 often3_i$
3. $\beta' x_i = \beta_0 + \beta_1 subscr_i + \beta_2 farmer_i + \beta_3 gourmet_i + \beta_4 natural_i$
 $+ \beta_5 club_i + \beta_6 mass_i + \beta_7 supermkt_i$
4. $\beta' x_i = \beta_0 + \beta_1 taste_i + \beta_2 fresh_i + \beta_3 local_i + \beta_4 env_i + \beta_5 safety_i + \beta_6 nutri_i$
 $+ \beta_7 consistent_i + \beta_8 price_i$

While there is no strict rule for the number of predictor variables in the logit model, we specified four models with four sets of predictors instead of one model with whole predictors to avoid the overfitting problem. We estimated the parameters by maximizing the following log likelihood function:

$$logL(\beta) = \Sigma[c_i log(\pi_i) + (1 - c_i) log(1 - \pi_i)] \tag{A11}$$

The maximum likelihood was estimated using the software package STATA 15 (StataCorp LLC, College Station, TX, USA).

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