CONSUMER ACCEPTANCE AND OPTIMIZATION STRATEGIES FOR SUSTAINABLE INDOOR AGRICULTURE: EXPLORING ATTITUDES, PREFERENCES, AND ECONOMIC-ENVIRONMENTAL TRADE-OFFS

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ABSTRACT

Indoor agriculture (IA) has emerged as a promising solution to address global challenges such as increasing food demand and limited natural resources. The potential benefits of IA as a sustainable agricultural production method have been widely discussed, but the industry's success hinges on consumer acceptance of IA technology and their willingness to consume leafy greens produced through this innovative approach. This dissertation aims to explore consumer attitudes and preferences towards IA, as well as to propose a comprehensive optimization model for sustainable IA systems in urban settings.

The first chapter focuses on understanding consumer acceptance of IA produce. By employing cluster analysis, distinct groups of U.S. leafy green consumers were identified, including "IA Skeptics," "IA Open," "IA Supportive," and "IA Engaged." The study reveals a strong positive consumer cluster with a broad willingness to consume IA produce, suggesting significant market opportunities for the IA industry. However, it also highlights the presence of consumers who have not yet formed a clear attitude towards IA technology. Consequently, the chapter suggests marketing strategies to expand consumer awareness and acceptance of IA produce.

The second chapter investigates consumer preferences and willingness-to-pay (WTP) for leafy green attributes, particularly in relation to different production methods, including IA, field farming, and greenhouses. Through a discrete choice experiment, preferences and WTP for attributes such as taste, freshness, nutrient level, and food safety were assessed among U.S. leafy green consumers. The study identifies significant preference heterogeneity, categorized into three latent classes: 'quality seekers,' 'price conscious,' and 'focused practicals.' Notably, preference heterogeneity is higher for production methods, indicating that consumers' preferences for IA

technology are still evolving. The chapter emphasizes that IA has the potential to achieve consumer acceptance but highlights the importance of understanding the varying WTP among different consumer segments.

The third chapter addresses the optimization of IA systems for economic and environmental sustainability. By employing a multiobjective optimization framework, the study proposes a comprehensive optimization model that integrates a plant growth module, a cost module, and a revenue module. The model aims to optimize both profitability and energy use efficiency of IA systems in urban settings, using decision variables such as production schedule, farm size, and farm location. The findings reveal the trade-offs between profit and energy use efficiency within a short production schedule window, emphasizing the need for fine-tuning the production schedule based on preferences related to these two objectives. Furthermore, the optimal location of IA farms is found to vary based on farm size, suggesting the need for tailored approaches rather than a uniform strategy.

By encompassing consumer acceptance, preferences, and optimization strategies, this dissertation contributes to the understanding and advancement of IA as a sustainable agricultural production method. The findings provide valuable insights for stakeholders in the IA industry, enabling them to develop strategies that enhance consumer acceptance, optimize IA systems, and promote sustainable food production for the growing urban population.

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CHAPTER 1

SEEDS OF INDUSTRY SUSTAINABILITY: CONSUMER ATTITUDES TOWARDS INDOOR AGRICULTURE BENEFITS VERSUS ITS ADVANCED TECHNOLOGY

1.1 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 (De Clercq et al., 2018; Despommier, 2009; Pinstrup-Andersen, 2018; *Research and Development Potentials in Indoor Agriculture and Sustainable Urban Ecosystems*, 2019). 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 (Van Gerrewey et al., 2022). 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 (Graamans et al., 2018; Kozai et al., 2006; Kozai, 2013). 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 (*Research and Development Potentials in Indoor Agriculture and Sustainable Urban Ecosystems*, 2019; Kozai, 2018). In parallel with research developments, the IA industry has grown at a fast pace in the United States and abroad (Agrilyst, 2016; Agrilyst, 2017; *2019 Global CEA Census*, 2019; *2020 Global CEA Census Report*, 2020).

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 (Van Gerrewey et al., 2022; Benke and Tomkins, 2017), 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 CO2 level, air temperature, and humidity (Zhang et al., 2019; Meng et al., 2020).

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 (Nelson, 1970; Darby and Karni, 1973), 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 (2009), 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 (Kozai, 2018).

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 (Cox et al., 2007; Frewer et al., 2011; Vidigal et al., 2015). 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 (Costa-Font et al., 2008; Hossain et al., 2008). 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 (Gifford et al., 2005; Ureña et al., 2008), but even organic produce sometimes faces rejection by consumers (Kim et al., 2018; Yue et al., 2009).

There has been a strand of literature investigating consumer acceptance of IA produce, but the findings have sometimes been inconsistent (Coyle and Ellison, 2017; Huang, 2019; Kurihara et al., 2014; Nishi, 2017; Yano et al., 2021). Coyle and Ellison (2017) and Nishi (2017) 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 (2017) 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. (2014) 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 (2017) used a sample of 116 participants from the University of Illinois campus and surrounding community, while Nishi (2017) used 116 non-student participants. Kurihara et al. (2014) studied housewives residing in Tokatsu Region. Yano et al. (2021) 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 (Huang, 2019; Bukenya and Write, 2007; Hoban, 1999; Bredahl, 2001; Verdurme and Viaene, 2001).

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.

1.2 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 (Blanck et al., 2008; Emanuel et al., 2012), while the latter might be due to easier access to online surveys (Hudson et al., 2004).

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.

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 (Despommier, 2009; *Research and Development Potentials in Indoor Agriculture and Sustainable Urban Ecosystems*, 2019; Van Gerrewey et al., 2022; Kozai, 2018; Benke and Tomkins, 2017; Zhang et al., 2019; Meng et al., 2020; Coyle and Ellison, 2017) 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 (Coyle and Ellison, 2017) . 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 (Siegrist and Hartmann, 2020) . 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.

1.3 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) (Mazzocchi, 2011), 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 (Ding and Xiaofeng, 2004; Josse, 2010).

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.

1.4 Results

1.4.1 PCA Analysis—Pro-IA, Unnatural, Knowledge Level

The PCA with Kaiser's varimax rotation (Kaiser, 1958) 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 (Choi et al., 2010). 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".

1.4.2 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 (2011) 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.

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.

1.4.3 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).

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.

1.4.4. 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.

1.4.4.1 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 (Wilks et al., 2019).

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" (Siddiqui et al., 2022).

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".

1.4.4.2 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 (Table 6 and Table 7).

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.

1.4.4.3 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 (Aprile et al., 2016). 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 (Van Gerrewey et al., 2022). Lowering the environmental impact of IA would likely be helpful to not only enhance environmental sustainability, but also improve the profitability of IA farms.

1.5 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 (Dawson, 2013). 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.

1.6 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 (Frewer et al., 2011). 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 (Vidigal et al., 2015; Costa-Font et al., 2008; Hossain et al., 2008), though the relationship between knowledge and acceptance must be disentangled carefully (House et al., 2004).

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 (Hossain and Onyango, 2004; Hossain et al., 2002; Veeman et al., 2005). 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: TABLES AND FIGURES

Table 1.1 Statistical summary of the sample socio-demographics and of the U.S. population (%).

		Sample (n=2,114)	U.S. population[a]
Age	18 – 25 (18 – 24)[b]	15.61	11.90
	26 – 35 (25 – 34)	18.35	17.85
	36 – 55 (35 – 54)	31.88	32.43
	56 – 65 (55 – 64)	15.37	16.64
	66 – 80 (65 – 79)	17.27	16.19
	Over 81 (Over 80)	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 degree	32.45	30.35
	Bachelor's degree or higher	41.39	30.60
Ethnicity/Race	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 ($/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	79.61	80.7
	Rural	20.39	19.3

Notes: [a] U.S. population estimates were obtained from U.S. Census Bureau's 2019 American Community Survey.
[b] Age brackets used for U.S. population in parenthesis.

Table 1.2 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.

Table 1.3 Consumer responses to attitude variables by four clusters.

Variables	IA Skeptical	IA Accepting	IA Supportive	IA Engaged
Observations (%)	651 (30.8)	529 (25)	628 (29.7)	306 (14.5)
Higher Quality‡	2.710 [a],***	3.214 [b],***	3.828 [c],***	4.670 [d],***
Less Labor‡	2.957 [a]	3.473 [b],***	3.815 [c],***	4.739 [d],***
Local Easier‡	2.839 [a],***	3.452 [b],***	3.997 [c],***	4.703 [d],***
Better Environment‡	2.730 [a],***	3.189 [b],***	3.895 [c],***	4.663 [d],***
Mainstream Future‡	2.954 [a]	3.543 [b],***	4.150 [c],***	4.712 [d],***
Unnatural/Artificial‡	3.296 [a],***	3.034 [b]	2.490 [c],***	4.559 [d],***
Confidence in knowledge of IA‡	3.401 [a],***	2.066 [b],***	3.978 [c],***	4.585 [d],***

‡Means from Likert scale running from 1 (Strongly disagree) to 5 (Strongly agree) with 3 being Neutral.

t-test significance level is represented by asterisks: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

[a,b,c,d] Different superscript shows the significant difference from Kruskal–Wallis test ($p<0.01$).

Table 1.4 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 B Table 1.9.

Level of willingness to consume IA produce	Accepting	Supportive	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***	0.094***
	(0.003)	(0.009)	(0.016)
Strongly agree	0.128***	0.358***	0.527***
	(0.016)	(0.017)	(0.016)
Observations	2,114	2,114	2,114

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Cluster membership of ‘IA Skeptics’ is omitted for the benchmark purpose.

Table 1.5 Average marginal effect of demographic characteristics on the likelihood of being in clusters.

VARIABLES	(1) Skeptics	(2) Open	(3) Supportive	(4) Engaged
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 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 $30,000/year)	-0.077***	0.012	0.091***	-0.022
	(0.025)	(0.025)	(0.027)	(0.021)
Third quarter ($30,000 - $60,000/year)	-0.066**	-0.009	0.089***	-0.005
	(0.029)	(0.028)	(0.030)	(0.023)
Fourth quarter (More than $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	2,114	2,114	2,114	2,114

Standard errors in parentheses. t-test significance level is represented by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Dependent variables in the model (1), (2), (3), and (4) are cluster membership for IA Skeptics, IA Open, IA Supportive, and IA Engaged respectively.

Generation X (41 – 55)[a], female, high school degree, first income quarter, and rural area were omitted as benchmark purpose.

[a]: Age in 2021.

Table 1.6 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	2,114	2,114	2,114	2,114

Standard errors in parentheses. t-test significance level is represented by asterisks: *** p<0.01, ** p<0.05, * p<0.1.
Dependent variables in the 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 as benchmark purpose.

Table 1.7 Average marginal effect of self-reported leafy green purchase source on the likelihood of being in clusters.

VARIABLES	(1) Skeptics	(2) Accepting	(3) Supportive	(4) Engaged
Food subscription or delivery system	-0.112***	-0.103***	-0.203***	0.169***
	(0.037)	(0.039)	(0.039)	(0.015)
Farmers markets	0.007	-0.074***	0.063***	0.001
	(0.022)	(0.021)	(0.022)	(0.015)
Gourmet food stores	-0.044	-0.090**	-0.008	0.047***
	(0.036)	(0.040)	(0.036)	(0.018)
Natural grocery stores	-0.019	-0.076***	-0.002	0.080***
	(0.023)	(0.023)	(0.023)	(0.014)
Club stores	-0.042	-0.037	-0.004	0.057***
	(0.027)	(0.025)	(0.026)	(0.015)
Mass merchandisers	-0.108***	0.007	0.035	0.045***
	(0.023)	(0.021)	(0.022)	(0.014)
Supermarkets	-0.071***	0.046*	0.078***	-0.064***
	(0.024)	(0.025)	(0.026)	(0.014)
Other	-0.111	0.021	0.145*	
	(0.083)	(0.073)	(0.079)	
Observations	2,114	2,114	2,114	2,082

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.

Table 1.8 Average marginal effect of self-reported leafy green attribute importance on the likelihood of being in clusters.

VARIABLES	(1) Skeptics	(2) Accepting	(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	-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	-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	2,114	2,114	2,114	2,114

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.

Figure 1.1 Methodological framework: attitudes towards indoor agriculture (IA) data were analyzed using a principal component analysis (PCA), two-stage cluster analysis (CA), and logit model.

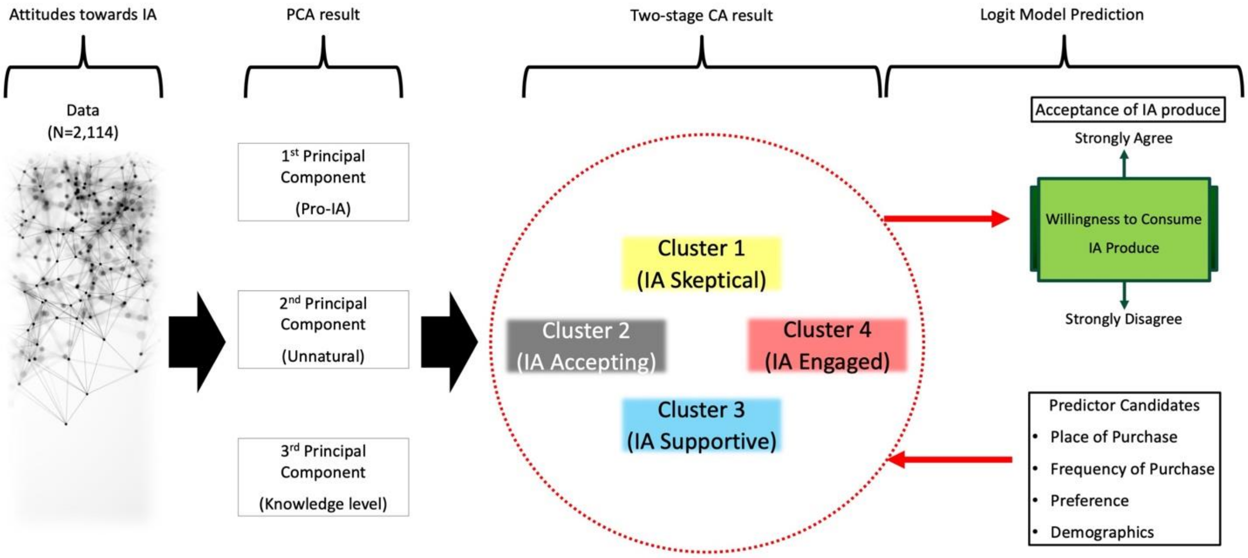


Figure 1.2 Scatter plot of the scores of the principal components of individual consumers on the 3-dimensional space of the principal components (PC). Yellow, black, blue, and red represent Skeptics, Open, Supportive, and Engaged, respectively.

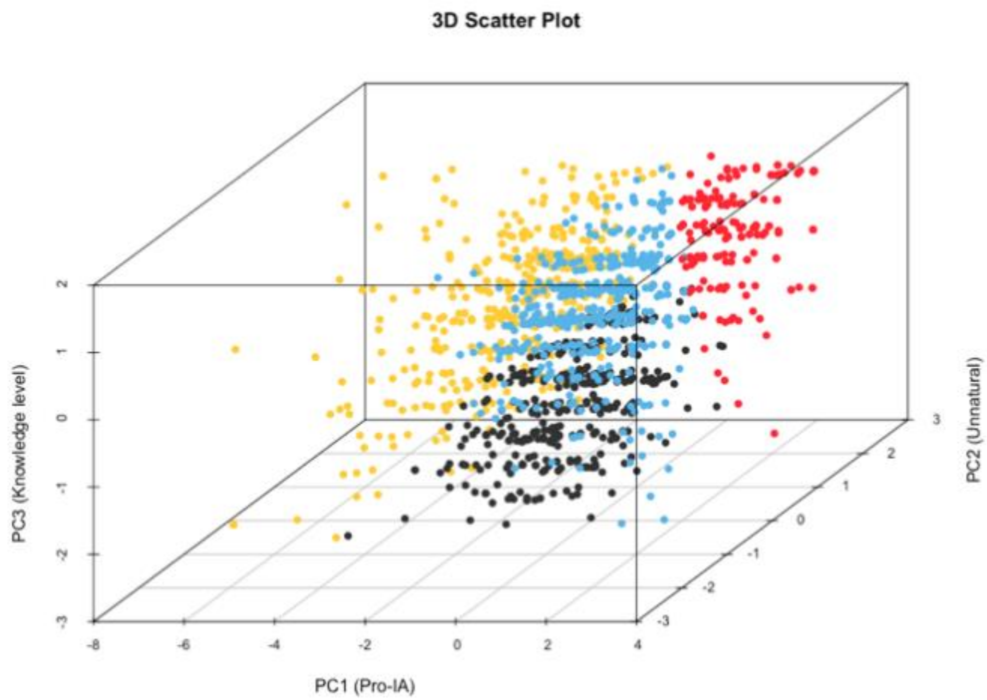
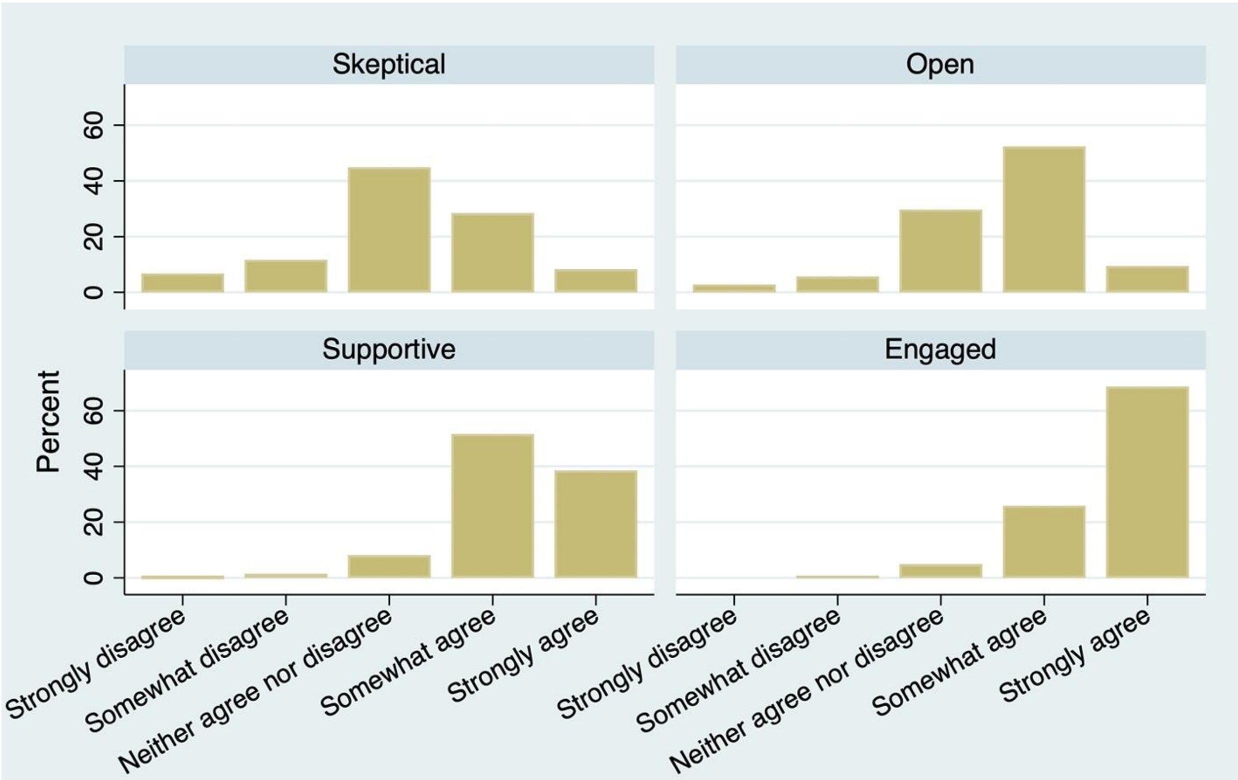


Figure 1.3 Willingness to consume IA produce by U.S. leafy green consumer cluster.



APPENDIX B: OLM SPECIFICATION

The theoretical framework was based on Lancaster's consumer theory (Lancaster, 1966). 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:

$$U_{ji} = V_{ji} + \varepsilon_{ji} \tag{B1}$$

where Vji is the deterministic portion and ϵji is the random component of the utility.

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

$$Z_i = (V_{Ii} + \varepsilon_{Ii}) - (V_{Ni} + \varepsilon_{Ni}) = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni}) \tag{B2}$$

Consumer i's choice ordering, which we denote as Yi, depends on Zi because the difference in utility represents the additional utility gain from choosing one against the other. Yi

is the observed choice ordering, respondent i's willingness to consume IA produce measured by a five-point scale of Likert-type question. Therefore, Yi becomes the degree of consumer acceptance of IA produce. In order to formulate the relationship between the observed choice ordering, Yi and Zi, we denote $\mu1$, $\mu2$, $\mu3$, and $\mu4$ as the cut-off points that are unknown to the researcher. In this approach, consumer i will strongly reject consuming IA produce (Yi=1) if $Zi\leq\mu1$, somewhat reject consuming IA produce (Yi=2) if $\mu1<Zi\leq\mu2$, neither reject nor accept consuming (Yi=3) if $\mu2<Zi\leq\mu3$, somewhat accept consuming IA produce (Yi=4) if $\mu3<Zi\leq\mu4$, and strongly accept consuming IA produce (Yi=5) if $Zi>\mu4$. Thus, we define Yi as follows:

$$Y_i = \begin{cases} 1 & if\ \ Z_i \leq \mu_1 \\ 2 & if\ \ \mu_1 < Z_i \leq \mu_2 \\ 3 & if\ \ \mu_2 < Z_i \leq \mu_3 \\ 4 & if\ \ \mu_3 < Z_i \leq \mu_4 \\ 5 & if\ \ \mu_4 < Z_i \end{cases} \tag{B3}$$

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:

$$\begin{aligned} P_{i1} = P(Y_i = 1) &= P[Z_i = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni}) \leq \mu_1] \\ &= F(\mu_1 - (V_{Ii} - V_{Ni})) \end{aligned} \tag{B4}$$

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:

$$\begin{aligned} P(Y_i = 2) &= P[\mu_1 < Z_i = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni}) \leq \mu_2] \\ &= F\big(\mu_2 - (V_{Ii} - V_{Ni})\big) - F\big(\mu_1 - (V_{Ii} - V_{Ni})\big) \\ P(Y_i = 3) &= P[\mu_2 < Z_i = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni}) \leq \mu_3] \\ &= F\big(\mu_3 - (V_{Ii} - V_{Ni})\big) - F(\mu_2 - (V_{Ii} - V_{Ni})) \end{aligned} \tag{B5}$$

$$P(Y_i = 4) = P[\mu_3 < Z_i = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni}) \leq \mu_4]$$

$$= F\big(\mu_4 - (V_{Ii} - V_{Ni})\big) - F(\mu_3 - (V_{Ii} - V_{Ni}))$$

$$P(Y_i = 5) = P[\mu_4 < Z_i = (V_{Ii} - V_{Ni}) + (\varepsilon_{Ii} - \varepsilon_{Ni})]$$

$$= 1 - F(\mu_4 - (V_{Ii} - V_{Ni}))$$

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

$$Z_i = \boldsymbol{\beta}'\boldsymbol{x}_i + v_i = \beta_1 Cluster2_i + \beta_2 Cluster3_i + \beta_3 Cluster4_i + v_i \tag{B6}$$

where xi = ($Cluster2i$,$Cluster3i$,$Cluster4i$), β = ($\beta1$,$\beta2$,$\beta3$), and vi is a stochastic error term. $Cluster2i$, $Cluster3i$, and $Cluster4i$ 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 $Cluster2i$=0, $Cluster3i$=0, and $Cluster4i$=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:

$$logL(\mu_k, \boldsymbol{\beta}) = \sum_{i=1}^{2114} \sum_{k=1}^{5} m_{ik} \log\left[F(\mu_k - \boldsymbol{\beta}'\boldsymbol{x}_i) - F(\mu_{k-1} - \boldsymbol{\beta}'\boldsymbol{x}_i)\right] \tag{B7}$$

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

Table 1.9 Estimated parameters in the OLM.

VARIABLES	Coeff. (SD)
Cluster membership	
IA Skeptics‡	-
	-
Accepting	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***
	(0.0909)
μ_3	0.480***
	(0.0782)
μ_4	2.911***
	(0.106)
Observations	2,114

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
μ_1,μ_2,μ_3,μ_4 are the estimated cut-off points.
‡ : Cluster membership of 'IA Skeptics' is omitted for the benchmark purpose.

APPENDIX C: LM SPECIFICATION

To denote the binary dependent variable, we define c_{ij} as the indicator variable, which is 1 if *i*-th respondent is in *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,

$$P(C_i = c_i) = \pi_i{}^{c_i}(1-\pi_i)^{1-c_i} \quad for\ c_i \in \{0,1\} \tag{C1}$$

which is a Bernoulli distribution.

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

$$\log \frac{\pi_i}{1-\pi_i} = \boldsymbol{\beta}'\boldsymbol{x}_i \tag{C2}$$

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

$$\pi_i = \frac{\exp(\boldsymbol{\beta}'\boldsymbol{x}_i)}{1+\exp(\boldsymbol{\beta}'\boldsymbol{x}_i)} \tag{C3}$$

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

$$\begin{aligned}\beta' x_i = \beta_0 &+ \beta_1 GenZ_i + \beta_2 Millennials_i + \beta_3 Boomers_i + \beta_4 Male_i + \beta_5 edulev1_i \\ &+ \beta_6 edulev3_i + \beta_7 edulev4_i + \beta_8 edulev5_i + \beta_9 edulev6_i + \beta_{10} incquar2_i \\ &+ \beta_{11} incquar3_i + \beta_{12} incquar4_i + \beta_{13} urban_i + \beta_{14} suburban_i\end{aligned}$$

$$\beta' x_i = \beta_0 + \beta_1 often1_i + \beta_2 often2_i + \beta_3 often3_i$$

$$\begin{aligned}\beta' x_i = \beta_0 &+ \beta_1 subscr_i + \beta_2 farmer_i + \beta_3 gourmet_i + \beta_4 natural_i + \beta_5 club_i + \beta_6 mass_i \\ &+ \beta_7 supermkt_i\end{aligned}$$

$$\beta' x_i = \beta_0 + \beta_1 taste_i + \beta_2 fresh_i + \beta_3 local_i + \beta_4 env_i + \beta_5 safety_i + \beta_6 nutri_i$$
$$+ \beta_7 consistent_i + \beta_8 price_i$$

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:

$$logL(\boldsymbol{\beta}) = \sum [c_i \log(\pi_i) + (1 - c_i) \log (1 - \pi_i)] \tag{C4}$$

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

CHAPTER 2

WHO IS WILLING TO PAY FOR LEAFY GREENS PRODUCED BY INDOOR AGRICULTURE? A COMPARATIVE CHOICE EXPERIMENT WITH U.S. CONSUMERS

2.1 Introduction

Agricultural technology innovators seek to create more sustainable food production methods for a growing population. In some agriculture sectors, producers gained efficiency and increased volume by specializing and centralizing operations in suitable climates. In the U.S., leafy green production is one prominent example: 91% of field-farmed iceberg lettuce and 97% of Romaine lettuce sold in the U.S. are grown in Arizona, California, and Florida before being trucked across the country (U.S. Department of Agriculture, 2022). However, despite the efficiency of economies of scale, this distribution system generates significant greenhouse gas emissions. In this context, indoor agriculture (IA) offers an environmentally sustainable alternative to large-scale leafy green production by producing closer to consumers in urban areas, even in regions with less favorable climates (Despommier, 2009). IA is similar to greenhouses in that greenhouses also control some environmental factors; however, IA is characterized by the exclusive use of artificial lighting systems which allow for growing beds to be stacked vertically. These unique features of IA make it possible to grow crops within sealed structures, where the environment factors affecting plant growth are fully controlled. In particular, IA enables production throughout the year, requires little to no pesticide, and improves resource use efficiency (Banerjee & Adenaeuer, 2014; Fukuda & Wada, 2019; Pennisi et al., 2019; Stein, 2021). IA is comparable with greenhouse production in terms of total cost (Eaves & Eaves, 2018) but outperforms greenhouses in resource use efficiency in the climate zones of the Netherlands and Sweden (Graamans, Baeza, van den Dobbelsteen, Tsafaras, & Stanghellini, 2018). IA farm systems also consume 90% to 95% less water than field farming operations (Stein, 2021). Further, IA growing structures can occupy ten times less land because they use vertical space; in other words, IA can multiply yield per area by 100 times compared with outdoor growing (Armanda, Guinée, & Tukker, 2019). Finally, indoor growers can use artificial lighting systems and control humidity, temperature, and other environmental growth factors to alter the maturation and characteristics of produce. These innovations include improving plant growth and fresh weight (Pennisi et al., 2019) as well as enhancing consumer-sought attributes such as color, taste, and crunchiness (Fukuda & Wada, 2019; Zhang, Whitman, & Runkle, 2019). Given the production opportunities afforded by IA technology, the industry holds much promise.

However, significantly higher capital and operating costs of IA systems impede growth in this industry (Agrilyst, 2016; Autogrow & Agritecture Consulting, 2019; Weidner, Yang, Forster, & Hamm, 2022). While literature focuses mainly on maximizing yield and minimizing operating costs of IA systems (Tong, Yang, & Shimamura, 2014; Touliatos, Dodd, & McAinsh, 2016; Benke & Tomkins, 2017), IA-specific consumer demand and revenue generation capability are understudied areas. These analyses are crucial to producers because the aforementioned productivity and resource efficiency gains associated with IA are necessary for profitability but insufficient to assure it. Market analysis are also necessary to identify the extent of IA's revenue-generating capabilities. In particular, IA may have an advantage over competing growth systems by attracting price premia for enhanced quality attributes such as nutrient levels, appearance, and taste of leafy greens (Bian, Yang, & Liu, 2015; Meng, Boldt, & Runkle, 2020).

Although IA technology can potentially attract price premia through the enhancement of quality attributes of leafy greens, consumer acceptance of innovative IA produce will likely vary across different consumer segments as novel food technology often face consumer rejection (J.

Costa-Font & Mossialos, 2005; M. Costa-Font, Gil, & Traill, 2008; De-Magistris & Gracia, 2016; Frewer et al., 2011; Hossain, Adelaja, Hallman, Onyango, & Schilling, 2008; Short et al., 2018; Yang & Hobbs, 2020; Yue, Zhao, & Kuzma, 2015). For example, some consumers view IA technology as significantly less natural than other production methods (Coyle & Ellison, 2017; Seong, Valle De Souza, & Peterson, 2023). However, experimental studies suggest that 'unnaturalness' perception is not likely the sole source of consumer rejection (Frewer et al., 2011). Also, some experimental evidence showed that lettuce consumer average willingness to pay (WTP) for production methods does not differ across production methods (Nishi, 2017; Short et al., 2018). Consumers are nevertheless likely to derive different levels of utility from leafy green attributes and, in turn, exhibit different WTP across different demographic classifications (Yu, Neal, & Sirsat, 2018; Gedikoğlu & Gedikoğlu, 2021).

The goal of this paper is to identify the revenue-generating capabilities of IA leafy greens through a comprehensive consumer preferences and willingness to pay analysis. Using U.S. representative sample, we investigate consumers reaction to leafy green quality attributes considering IA as an alternative production method. This paper addresses the lack of consensus in consumer rejection towards IA produce and identifies the heterogeneity across different groups of consumers. Specifically, it presents a study that (i) identifies consumer preferences for leafy green attributes in a comparative analysis between IA, greenhouse (GH) and field farming (FF) production methods; (ii) estimates consumer WTP for leafy green quality attributes IA technology could potentially enhance and the extent to which their perception of production systems affects WTP; and (iii) measures heterogeneity between groups of consumers in terms of their reported willingness to consume and WTP for IA-produced leafy green with given attributes.

This paper contributes to the literature by providing empirical evidence that a majority of U.S. consumers is willing to pay a premium price for IA produce and its enhanced quality attributes by using a representative sample of 2,114 U.S. leafy green consumers. To our knowledge, an U.S. representative sample has not yet been used in the literature, and therefore U.S. consumer preference heterogeneity has not been identified in past studies. Also, our extensive sample allowed us to investigate various demographic subgroups of consumers. Specifically, we investigated difference in WTP across generations and living area, which will be especially helpful to inform the industry about potential market niches. These results will describe how attributes and production technologies affect consumer WTP, and finally inform industry and policymakers of current U.S. consumer IA technology preferences. Furthermore, these results will promote the growth of an industry poised to reduce agriculture's environmental impact while growing fresh food closer to consumers.

2.2 Leafy Green Consumers Survey Data

We collected consumer survey data in July and August 2021 using the QualtricsXM online survey platform. To obtain responses from consumers in the market for leafy greens, we targeted adults (18 years or older) living in the United States who purchased leafy greens within the three months of taking the survey. A soft run of the survey was initially distributed to 200 online respondents registered with Qualtrics and to industry and research collaborators to test the survey for appropriate flow, as well as accuracy, relevance, and clarity of questions. Qualtrics controlled the final distribution to ensure a demographically- and geographically-balanced sample, and to limit reporting to only reliable responses based on their inhouse verification methods. In total, we acquired 2,114 valid responses for the present study.

The sample is a good representation of the U.S. demographics, although slightly overrepresenting higher education levels in relation to the U.S. population (Table 2.1). This is, however, a common finding among online surveys because online survey methods are more approachable among the more educated (Hudson, Seah, Hite, & Haab, 2004). Another source of this bias might be the fact that leafy green consumers differ from the U.S. population in general. For example, our sample is slightly biased towards female participants, which may reflect that women are more likely to consume leafy greens than men (Blanck, Gillespie, Kimmons, Seymour, & Serdula, 2008). Despite slight biases, the sample closely reflects the characteristics of the U.S. population (U.S. Census Bureau, 2019). We collected demographic information including age, gender, education, ethnicity, marital status, household size, household income, and living area.

Based on ages in 2021, we classified four generation cohorts: generation Z (age 18 – 25), Millennials (age 26 - 40), generation X (age 41 – 55), and baby boomers (age 56 and over). We classified generation following Page and Williams (2015) as their research is to understand consumer behavior and marketing strategies based on U.S. generations. Also, we considered importance of generation as a predictive variable to understand the acceptance of novel food technology (Okumus, Dedeoğlu, & Shi, 2021; Öz, Unsal, & Movassaghi, 2018; Shaw & Mac Con Iomaire, 2019).

In the survey, we asked respondents if they would be willing to eat leafy greens grown on an IA farm using a 5-point Likert scale question (1 indicated ‘strongly disagree’ and 5 indicated ‘strongly agree’). We define willingness to consume (WTC) equal to 1 if a respondent strongly agreed to this statement and 0 otherwise. About a quarter of the sample (26.3%) strongly agreed to this statement.

2.3 Methodology

This paper uses a hypothetical choice experiment to investigate consumer preferences for IA production of leafy greens. Hypothetical choice experiments (CE) are frequently used in the literature to estimate consumer preferences (Lusk, Roosen, & Fox, 2003; Lusk & Schroeder, 2004; Gao & Schroeder, 2009; Van Loo, Caputo, Nayga, Meullenet, & Ricke, 2011), but the intrinsic hypothetical bias concern has been questioned in the literature, fostering the strategies to overcome such bias (Loomis, 2014). Although past research efforts revealed that some strategies (e.g. oath, cheap talk, and consequentiality) can be successful in some situation, but unfortunately, none has been accepted as ideal in the literature. Nevertheless, we applied several tactics that could be useful to mitigate hypothetical bias in present study. Firstly, we strictly controlled number of words presented to the respondents during the CE to minimize fatigue, because it can increase error as a respondent face multiple choice tasks repeatedly (Bradley & Daly, 1994; Noussair, Robin, & Ruffieux, 2002). Considering the cognitive load of our choice task, we didn't use cheap talk script (Aadland & Caplan, 2006). Instead, we utilized illustrations and images to convey information and reduce cognitive load (Cherchi & Hensher, 2015; Fang et al., 2021). Secondly, we provided a no-buy option in the experiment to enhance realism for each choice task, lowering hypothetical bias (Batsell & Louviere, 1991; Penn & Hu, 2021). Although inclusion of no-buy option in our experiment was based on consideration of real leafy green purchase scenario and past food choice literature, the effect of having a no-buy option and the reason for choosing this alternative becomes subject for further research (Kontoleon & Yabe, 2003; Veldwijk, Lambooij, De Bekker-Grob, Smit, & De Wit, 2014). Although hypothetical CEs may overestimate the probability of purchasing an alternative (Lusk & Schroeder, 2004), the methodology allows consumers to simultaneously consider multiple attributes of a good in a simulated purchasing scenario and facilitates the introduction of attributes or alternatives unavailable in extant markets. Thus, hypothetical CE is useful to identify revenue generating ability of IA produce by estimating WTP for attributes of IA produce in a comparison framework between existing agricultural production methods. Since IA is an emerging sector, there exists only limited data regarding IA produce consumption and market prices, none of which are publicly available to our knowledge. Further, USDA (United States Department of Agriculture) does not report leafy green production data differentiated by production method and scanner data for IA produce are difficult to obtain. Given the intractability of non-hypothetical options, we opted for a hypothetical CE. Also, we opted for gathering primary data through a survey due to the lack of publicly available data for IA produce.

Our data analysis employs a sequence of models, including random parameter logit models (RP) to allow identify the correlation between attribute parameters, and latent class multinomial logit models (LC) to estimate preference heterogeneity among leafy green consumers. RP is also used to estimate WTP for attributes of leafy greens and price elasticity for our national sample as well as subsamples of interest. In addition, we identify latent preference classes using LC methodology and name the resulting classes based on the coefficients and WTP estimates for attributes of leafy greens.

2.4 Discrete Choice Experiment Design

We selected green leaf lettuce for this study due to its popularity among consumers and prominence among IA growers (Agrilyst, 2017). Compared to other leafy greens, lettuce is particularly suited for IA cultivation given its high ratio of edible mass per plant, relatively small size and fast growth cycle. We chose a labeled design across production methods so that the choice task would imitate a real purchasing scenario at a local supermarket including leafy green attributes and levels (Table 2.2). In each choice task, respondents faced four alternatives: field farmed (FF), greenhouse-grown (GH), indoor agriculture (IA), and a no-buy option. In addition to price, we varied four attributes over each alternative: freshness, taste, nutrient level, and food safety. We chose this bundle of attributes based on three factors: importance to consumers, possibility of attribute improvement through IA technology, and respondent fatigue. First, we referenced previous studies (Gilmour, 2018; Zhang et al., 2019; Meng et al., 2020) to identify the attributes leafy greens consumers find most important. We supplemented our findings in the literature with a preliminary survey of leafy greens consumers and industry stakeholders. Second, we considered whether IA technology ability to enhance those leafy green quality attributes could meaningfully alter consumer WTP for leafy green enabling potential growth of IA industry. Finally, we considered respondent fatigue. Since our CE design requires respondents to consider multiple attributes with varying attribute levels simultaneously, presenting many leafy green quality attributes would make choice task too complex, inducing higher opt-out rates (Oehlmann, Meyerhoff, Mariel, & Weller, 2017). We conducted a pilot survey to detect unusual signals which might be induced by complex choice tasks. Based on the preliminary result from piloted survey, we maintained the experimental design.

By limiting the number of attributes and decreasing respondent fatigue, we made a behavioral assumption that respondents will observe and evaluate all attributes when making a choice. However, it is still possible that respondents do not attend to certain attributes which can be implied by observed choices. To detect the presence and extent of attribute non-attendance (ANA) behavior, we tested several ANA strategies that are likely to exist through inferred ANA approach by using equality-constrained latent class (ECLC) framework proposed by Scarpa et al. (2009). We made assumptions on ANA strategies based on common characteristics of attributes.

For example, we assumed that one is more likely to ignore all production methods rather than one specific method. We were not able to observe model fit improvement using ECLC models.

We selected price levels for FF lettuce based on the retail price report by USDA in 2021 for lettuce commodity market (U.S. Department of Agriculture, 2021). The lack of formally reported market prices for GH and IA-produced premium lettuce at the time of this work led us to collect online prices from select U.S.-based chain grocery stores' websites (e.g., Wholefoods, Meijer, Kroger, Aldi), in September 2020. Our search included products advertised as differentiated produce, ready for consumption. We specify the same price range for the IA and GH alternatives in this study given their ability to achieve comparable quality levels within the considered set of attributes.

The experiment provides information to the survey respondents about relative levels for each of the targeted attributes (Figure 2.1). Beyond the photos to distinguish production methods (Figure 2), levels of each quality attribute next to the produce image were the sole information provided for making a purchase decision. The source of the information was not presented in order to avoid an obviously artificial label. Nutrient and safety labels do not exist currently in the IA marketplace due to absence of standards specifically for IA produce that is regulated by government agencies. Taste and freshness cannot be directly experienced at purchase, and all sellers have incentive to use only positive labels for these attributes. Each attribute level was given a descriptor consistent with prior research efforts (Araya, Elberg, Noton, & Schwartz, 2022; Miller & Cassady, 2015; Ravaioli, 2021; Kershaw et al., 2019). In addition, they were reviewed and approved by the project's industry collaborators. When designing level descriptors, we assumed a linear relationship between the leafy green quality attribute levels and utility. Taste, freshness, and nutrient level attributes were measured cardinally on a scale from 1 to 3 as the attribute levels were represented by a discrete number of descriptors, with larger numbers representing higher quality. In this reason, we assigned score of 1, 2, and 3 to levels of taste, freshness, and nutrient level attributes, the estimation result of willingness to pay for the attributes should be interpreted based on our scoring assumption. For taste and freshness, the numbers 1, 2, and 3 correspond with the descriptors presented to survey respondents 'ok', 'good', and 'very good', respectively. For the nutrient level attribute, the numbers 1, 2, and 3 correspond to the absence of a descriptor, a '20% more' descriptor, and a '50% more' descriptor, respectively.

By treating ordinal variables as continuous values instead of categorical variables, we gain an advantage by preserving the natural ordering of the information. However, we acknowledge that we cannot quantify how much better consumers perceive 'good' to be relative to 'ok.' This choice limits the interpretations and applications of our WTP estimates because a one unit increase or a one percent change does not correspond to an established metric. Despite this limitation, our simplifying assumption reduces the number of parameters to estimate in RP and LC, allowing us to investigate correlation patterns among a reasonable number of parameters.

We employed a fractional factorial orthogonal design approach to generate an efficient experimental design and limit the amount of choice tasks for respondents. Orthogonal design was chosen mainly because it minimizes correlation between attribute levels (Louviere, Hensher, & Swait., 2000). Although orthogonality is purely a statistical property rather than a behavioral property (Rose & Bliemer, 2009), we adopted this design approach for it has been a mainstream in stated choice experiment literature, providing empirical evidence of usefulness of orthogonal designs to elicit consumer behavior. To incorporate all three of the production methods into our analysis, we chose a labelled design. Using Ngene version 1.2.0 (ChoiceMetrics, 2018), we obtained a simultaneous orthogonal design with 36 choice tasks. This design achieves orthogonality both within each alternative and across alternatives as well as an efficient design with a D-error of 0.064. Since completing 36 choice tasks would be a demanding job for respondents, we blocked the design into six sets of six choice tasks. Each respondent was randomly assigned to one of the six blocks of choice tasks. Within each block, we randomized each of the six choice tasks to avoid ordering effects. Within each choice scenario, the position of labeled alternatives IA, GH, and FF were randomized. The no-buy option always came last.

In formatting the choice experiment, the image of green leaf lettuce was used to inform survey participants of the subject of choice task. We used an unpacked lettuce image throughout the choice experiment because different packaging styles are used for IA, GH, and FF produce in retail markets. Differences in packaging could affect leafy green consumers utility levels (Dawson, 2013) and is not attribute of interest in the present study. Also, we chose to convey attributes and attribute levels using images, symbols, and text so respondents could easily recognize differences between the alternatives. In addition, our survey presented respondents with a brief description and image of each of the three production methods (Figure 2.2) to briefly remind respondents of the main features of each production method and minimize hypothetical bias. We chose the representative IA image to emphasize the use of vertical space and artificial lighting, which are the most distinctive features of this production system. We provided minimal information about each production method before presenting the choice tasks because information effects lie outside the scope of this paper. However, any information that is provided before the experiment can affect the result of the experiment as observed in Coyle and Ellison's

(2017) study of WTP for IA produce with information treatment effect: respondents may build incorrect expectations even when provided with extensive information.

2.5 Econometric Modelling

The present study uses choice experiment to investigate green leaf lettuce choice problem which is consistent with random utility theory (McFadden, 1973) and Lancasterian consumer theory (Lancaster, 1966). The former established consumers as rational actors and making choices to maximize their utility subject to budget constraints, while Lancaster proposed that consumers derive utility from the attributes of goods instead of the good itself. We therefore assume that leafy green consumers are utility maximizers, and choose a given leafy green produce based on the total utility they derive from a bundle of attributes. The representative leafy green consumer n's utility can be represented with the deterministic component (V_{nj}), which is observed by the researcher, and the stochastic component (ε_{nj}), which is not observed by the researcher (Train, 2009):

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{2.1}$$

where U_{nj} is the utility derived by leafy green consumer *n* from choosing green leaf lettuce alternative *j* from a finite set of *J* alternatives. In the present study, V_{nj} is specified as a linear combination of the attributes of leafy greens:

$$V_{nj} = \beta_j + \beta_1 Price_{nj} + \beta_2 Taste_{nj} + \beta_3 Freshness_{nj} \tag{2.2}$$

$$+\beta_4 NutLev_{nj} + \beta_5 Safety_{nj}$$

where β_j represents a parameter attached to the alternative specific constant for IA, GH, and FF; $Price$ represents the level of price; $Taste$, $Freshness$, and $NutLev$ represent the level of taste, freshness, and nutrition respectively; $Safety$ represents food safety label. Three production methods are dummy coded as they are treated as alternative specific constants, and no buy option was omitted for the baseline purpose. $Safety$ is effects coded, equal to 1 if the food safety label was presented and -1 otherwise. $Price$ is coded by using five price points ranging from 1.9 to 5.9. $Taste$, $Freshness$, and $NutLev$ are coded by using scale of 1 to 3 that were assigned to three levels of ordered categories.

We assume that leafy green consumers choose the alternative, a set of attributes, to maximize utility. The probability that consumer *n* will choose the alternative *j* over *i* from choice set, C_n, can be written as follows:

$$P_{nj} = Prob\left(\beta' x_{nj} + \varepsilon_{nj} > \beta' x_{ni} + \varepsilon_{ni};\ \forall i \in C_n\ with\ i \neq j\right) \tag{2.3}$$

The error parameter, ε_{nj}, is unknown and assumed independent of β and x_{nj}. We assume that it follows type 1 extreme value (EV) distribution, independently and identically distributed (iid) over consumers and alternatives. This assumption yields the multinomial logit (MNL) model with logit choice probability that a consumer *n* chooses alternative *j*:

$$P_{nj} = \frac{\exp\left(\beta' x_{nj}\right)}{\sum_{i=1}^{J} \exp(\beta' x_{ni})} \tag{2.4}$$

2.6 Choice Experiment Analysis: Identifying Preference Heterogeneity Among Leafy Green Consumers

The primary interest of the present study is to investigate consumer WTP for IA-grown lettuce and to identify potential niche markets. We thus consider the extent and source of preference heterogeneity among leafy green consumers. While multinomial logit (MNL) models are widely used in the choice experiment literature to describe choice behavior, MNL models are restrictive (Phanikumar & Maitra, 2007) in that consumers are assumed to be homogeneous in terms of taste in the population (Van Loo et al., 2011) and therefore (i) do not allow random preference heterogeneity, (ii) cannot include correlation across alternatives and over repeated choices, and (iii) impose disproportionate substitution patterns. Random parameter (RP) logit models and latent class (LC) logit models are instead widely used to investigate consumer preference heterogeneity (Tonsor, Olynk, & Wolf, 2009) as they allow for individual-level and group-level variation in consumer preferences for choice specific attributes (McFadden & Train, 2000).

In RP models, the parameter of interest β is assumed to be an individual specific random parameter vector that is distributed in the population according to some parametric distribution. The present study assumes all non-price elements of β follow a normal distribution and specifies a non-random price coefficient following Revelt and Train (1998). This will provide for estimated WTP to be distributed normally (Lusk et al., 2003), and to avoid implausible estimates of individual price coefficient.

The present study allows correlation between random parameters (Revelt & Train, 1998; Train, 2009; Hensher, Rose, & Greene, 2015) to reflect the relationships between consumer preferences for different leafy green attributes. We assume a correlation pattern among the coefficients for production methods as well as between the production methods and other leafy green quality attributes. For example, consumers might consider IA a closer substitute for GH than FF. Considering such possibility, we estimate the lower-triangular Cholesky matrix for the parameters following Revelt and Train (1998).

Unlike RP models, LC models allow several classes of preferences to exist within a sample. Let subscript c denote class, where different preferences are represented by different values in the marginal utility parameter vector, β_c, for each class. We use an MNL model within each class, and thus face the restrictions of MNL model within each class[1]. However, LC models

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[1] We also estimated a random parameter logit approach to assigning respondents to each latent class to investigate the presence of within-class heterogeneity. When we considered three RP-assigned classes, the standard deviations

allow for preference heterogeneity by letting β_c vary across classes. LC models estimate the probability an individual would belong to each class with a class assignment probability model; in our analyses this is a MNL model. In the maximum likelihood estimation process, the joint probability of a consumer belonging to a certain class and the probability of a consumer choosing a lettuce alternative yields the likelihood function.

In LC models, the unconditional probability of consumer n's sequence of choices is as follows:

$$P_n^{LC} = \sum_{c=1}^{C} \pi_{nc} \prod_t \frac{\exp\left(\beta_c{}' x_{njt}\right)}{\sum_{i=1}^{J} \exp\left(\beta_c{}' x_{nit}\right)} \tag{2.5}$$

where π_{nc} is the class assignment probability that consumer n belongs to class c. The MNL class assignment probability model is:

$$\pi_{nc} = \frac{\exp\left(\theta_c{}' z_n\right)}{\sum_{c=1}^{C} \exp\left(\theta_c{}' z_n\right)}, \qquad \theta_C = 0 \tag{2.6}$$

where z_n is a set of covariates that affect class membership, and θ_c is the associated parameter vector to be estimated. We use an indicator variable for consumer willingness to consume (WTC) IA produce to investigate whether the level of consumer acceptance of IA technology affects preference heterogeneity. WTC equals one if a consumer reported strongly agreeing with the statement "I am willing to consume leafy greens grown in IA farms" and zero otherwise. The parameter vector for the last class, θ_C, is normalized to a zero vector for model identification. The maximum likelihood estimator can be computed by finding the C sets of marginal utility parameter vectors (β_c) and the C-1 sets of latent class parameter vectors (θ_c) which maximize the log-likelihood (LL) function:

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within each class were not statistically significant, providing evidence against within-class heterogeneity. Therefore, we prefer a MNL class assignment approach for LC estimation.

$$LL = \sum_{n} ln(P_n^{LC}) \tag{2.7}$$

2.7 WTP for Attributes of Leafy Greens and Price Elasticity

Estimates from the RP and LC specifications provide different insights into the WTP and price elasticities across the full sample, and subgroups of the full sample. Using our RP models, we obtain WTP and price elasticity estimates to describe the average preferences across the population and within demographic groups of interest. We also investigate WTP and price elasticity for each latent classes identified by our LC specification. Since individual consumer's class membership is unknown but latent, we sort individual consumers into classes using conditional (posterior) estimates of the individual class probabilities. Specifically, consumer n is sorted into the class to which they are assigned the highest conditional class probability. Then, WTP and price elasticity are estimated by applying MNL models within each class.

This paper computes mean WTP for a leafy green attribute ($WTP_{\text{Attribute}}$) following previous studies (Morrison, Bennett, Blamey, & Louviere, 2002; Gracia, Loureiro, & Nayga, 2009; Van Loo et al., 2011):

$$WTP_{Attribute} = -\frac{\frac{\partial U_{njt}}{\partial Attribute}}{\frac{\partial U_{njt}}{\partial Price}} \tag{2.8}$$

where WTP for a leafy green attribute is, ceteris paribus, the premium that a consumer is willing to pay for a one unit increase in a leafy green attribute while maintaining the same level of utility.

We investigate consumers' behavior using price elasticity which is useful to predict the change of choice probability in response to a change in price. Price elasticities measure the percentage change of the probability of choosing an alternative if there is one percent change in the price of an alternative, ceteris paribus. Price elasticity ($E^{P_{ni}}_{price_{nj}}$) is calculated as follows:

$$E^{P_{ni}}_{price_{nj}} = \frac{dP_{ni}}{dprice_{nj}} \cdot \frac{price_{nj}}{P_{ni}} \tag{2.9}$$

where P_{ni} is the probability to consumer n chooses alternative i, and $price_{nj}$ is the price of alternative j. To compute class-specific WTP and price elasticity estimates, we apply Bayes' theorem to obtain conditional (posterior) estimates for individual-specific class probability (Hensher, Rose, and Greene, 2015). We construct the standard errors and confidence intervals for the estimated WTP and price elasticities according to Krinsky and Robb's bootstrapping method with 1,000 random draws (Krinsky & Robb, 1986).

2.8 Results and discussion

Both the RP and LC models yield significant, presenting positive mean coefficients for Taste, Freshness, Nutrient level, and Food safety (Table 2.3). These results indicate leafy green consumers derive positive utility from each of these four quality attributes, assigning, on average, higher values to taste and freshness, consistent with previous studies (Bonti-Ankomah & Yiridoe, 2006; Gilmour, 2018).

Unlike the taste, freshness, nutrient level, and food safety attributes, the estimated coefficients for production methods vary significantly across the two models. In fact, as seen in Figure 3, the results from RP suggest significant preference heterogeneity across three production methods with standard deviation of the marginal utility parameters significantly larger than those of taste, freshness, nutrient level, and food safety attributes. This implies less consensus between consumers regarding their preferences for production methods. Nascent, still-forming preferences provide one interpretation of this result. This is somewhat expected considering IA represents a new concept to most consumers. A competing explanation could be that consumers just do not care much for production method at this time.

The estimated Cholesky matrix associated with the RP model (Appendix B) further explains the structure of the heterogeneous preferences explored above. The diagonal elements of the Cholesky decomposition matrix represent the level of heterogeneity sourced from each random parameter without confounding from cross-product correlation, while the below-diagonal elements of the matrix represent the amount of cross-product correlation (Hensher et al., 2015). All standard deviation estimates are statistically significant, but only the IA, FF, Nutrient level, and Food safety diagonal elements exhibit statistical significance. This indicates that the preference heterogeneity we observe, in terms of spread around the mean for GH, taste, and freshness, are not due to the preference heterogeneity for the attribute itself but arise due to cross-product correlation. The observed statistical significance of the below diagonal estimates of the matrix indicates some cross-product correlation (Hensher et al., 2015) and suggests a positive relationship between IA and three attributes: taste, freshness, and nutrient level. However, both consumer behavior and scale heterogeneity can drive these correlations and it is not feasible to empirically disentangle the two effects (Mariel & Artabe, 2020).

The differences between the attribute coefficients of the three latent classes reinforce the preference heterogeneity evidenced in the RP model, especially with respect to production methods (Table 2.3). The estimated class probability is highest for the first latent class (55.1%), followed by the second (26.3%) and the third class (18.6%). The first latent class is the least price sensitive as the estimated price coefficient is smallest. As shown by significant, positive coefficients for all non-price attributes, the members of this class value not only quality, but also production methods. These results imply that most of the population derives utility from knowing how their leafy greens are produced. Also, this class exhibits the highest WTP values for all green leaf lettuce attributes compared to other classes (Table 2.4). Based on these defining characteristics, we refer to members of the first latent class as 'quality seekers'.

In contrast, the second latent class is much more price sensitive with the most negative price coefficient of the three latent classes. Though consumers in this class obtain more utility from production method labels, they exhibit lower WTP for the green leaf lettuce attributes than the first class. Since price sensitivity defines these consumers, we refer to members of this class as 'price conscious'.

The most distinguishing feature of the third latent class is that consumers in this class derive negative utility from production methods, indicating that they prefer the no-buy option to any of the alternatives bearing production method information. However, consumers in this class still derive utility from quality attributes. Specifically, relative to other classes, the taste and freshness coefficients are higher and the nutrient level coefficients are lower. We hypothesize that consumers in this class represent practical buyers who are focused on a limited number of attributes. Taste and freshness seem to matter most to these consumers, while additional production method information is not helpful to their decision-making process. Hence, we refer to this class as 'focused practicals'. Consumers in this latent class are moderately price sensitive because price coefficient for this latent class falls between the estimates of the first and second latent classes. Demographic information of three latent classes is in Appendix C.

To investigate whether attitudes toward IA explain some of the preference heterogeneity, we include a dummy variable for willingness to consume (WTC) in the class probability model. We find that a strong positive attitude towards consuming IA produce increases the likelihood of belonging in the first latent class of 'quality seekers' (statistically significant at 1% level). This finding is consistent with the fact that 'quality seekers' have the highest WTP for IA of the three latent classes. However, 'quality seekers' do not prioritize IA over FF or GH when they face a lettuce purchasing choice scenario. This indicates that studying consumer attitude towards IA without considering the other production methods could yield misleading results.

Among our various specifications, the more flexible RP and LC models produce better fit in terms of log-likelihood, normalized AIC, BIC, and modified AIC (AIC3) (Bozdogan, 1993) criterion than the MNL (Table 2.5). Further, the correlated RP model improves model fit relative to the standard RP approach. The choice of number of classes for LC was primarily based on AIC3 as it is known to outperform other model selection criteria for LC models (Dias, 2006). We also considered the usefulness of the estimation result when choosing the number of classes. The model fit improves as we increase the number of classes, implying that allowing more heterogeneity in LC yields better model fit. However, LC with more than three classes yields a latent class with less than 5% class probability and statistically insignificant coefficient estimates. For these reasons, we focus only on results from the RP model with correlated parameters and LC model with three classes.

2.8.1 Price Elasticity and Willingness to Pay Estimates

We used the LC and RP models to obtain estimates of the average price elasticities over the whole sample using RP model (Table 2.6). Direct price elasticities, which measure the effect of price changes in an alternative on its own alternative's choice probability, show that all three production methods are inelastic to their own price change as shown by the coefficients lower than 1. Specifically, the direct price elasticity for IA alternative is estimated to be -0.931, meaning that a 1% increase in the price of IA alternative decreases the probability of choosing IA alternative by 0.931%. The FF direct price elasticity was more than three times lower than those of IA and GH (-0.242 versus -0.931 and -0.870, respectively). The cross-price elasticities, which measure the effect of a change in the price of an alternative on the probability of choosing a different alternative, indicate that consumers consider IA a substitute for GH and vice versa. In particular, when the price of GH increases by 1%, the probability of choosing IA is greater than that of choosing FF (0.334% and 0.182% respectively). However, if the price of FF increases by 1%, the probability of choosing either GH or IA increases by a similar amount (0.257% and 0.256% respectively), indicating that IA and GH are equally substitutable for FF.

We also found that the price elasticities vary significantly across the 'quality seekers', 'price conscious', and 'focused practicals' (Table 2.7). 'Quality seekers' are the most price inelastic, regardless of production method. This result is consistent with expectations since these consumers are the least sensitive to price and the exhibit the highest WTP estimates for all attributes. The estimated direct price elasticity of IA alternative for 'quality seekers' is -0.418, meaning that the probability of choosing IA alternative decreases by only 0.418% if the price of IA alternative increases by 1%. The direct price elasticity of IA for 'price conscious' and 'focused practicals' are -6.779 and -2.467, respectively, meaning that unlike 'quality seekers', their purchasing behavior changes significantly with price changes.

2.8.2 Willingness to Pay across Demographics

The size of WTP for production methods varied significantly across the generations (Figure 4). WTP for IA was highest for millennials, lowest for baby boomers, and statistically insignificant for Generation Z[2] (Gen Z). Although we cannot conclude that Gen Z's WTP for IA differs from zero, it appears that WTP for IA is not uniformly higher among younger generations.

[2] The sample frame included respondents 18 years of age and older. Many members of Gen Z were too young to participate in this study.

WTP for leafy green attributes also differs across different living area, varying significantly across urban-, suburban-, and rural-dwelling respondents (Figure 2.5). Results indicate that respondents living in urban areas are willing to pay more for IA than others in suburban or rural areas. This is a promising result for the IA industry as it aims to grow crops near urban consumers instead of transporting produce thousands of miles away (Kalantari, Nochian, Darkhani, & Asif, 2020). Expanding IA farms in urban areas may be costly, however these findings suggest a substantial premium in urban markets could justify profitable development in cities.

2.9 Conclusions

In this paper, we conducted a hypothetical choice experiment using a sample of 2,114 U.S. leafy green consumers to investigate preference heterogeneity for green leaf lettuce attributes, including production systems, and quality attributes. Our results provide strong evidence of preference heterogeneity for leafy green attributes, and it is represented by three distinctive latent classes which we named 'quality seekers', 'price conscious', and 'focused practicals', according to preference rankings. We find a significantly higher degree of preference heterogeneity towards production methods relative to the quality attributes of taste, freshness, food safety, and nutrient level. We hypothesize that U.S. preferences for IA are still being formed given that IA is an emerging concept, which in turn disrupts existing preferences about traditional growing systems. For the IA producers, this implies that there is an opportunity to crystallize consumer preferences for IA.

On average, consumer WTP for IA leafy greens is no higher than WTP for GH or FF leafy greens. However, averages alone often belie the underlying structures of heterogeneous preferences and yields misleading result. Once latent classes were identified within the sample, our results indicate that 'quality seekers', who account for 55.1% of population, are willing to pay $3.81/4.5oz for IA-grown green leaf lettuce, and their choice of IA produce are inelastic to its price change unlike other groups of consumers. In other words, a majority of leafy green consumers are willing to spend a significant premium for IA produce and their choice of IA would relatively stable to its price change. The estimated percentage premium for IA grown green leaf lettuce is 131% even if the calculation of the premium is based on the maximum commodity lettuce price ($2.90/4.5oz) used in the choice experiment. Considering that IA production systems could be regarded negatively (i.e. as an unnatural way of growing crops,) this result is promising for the future of IA industry.

The preference heterogeneity observed here can be associated with consumer attitudes towards IA. As expected, our results show that consumers with strong positive attitudes towards IA are more likely to be 'quality seekers' and demonstrate the highest WTP for IA produce. However, 'quality seekers' are still willing to pay more for the green leaf lettuce grown in GH or FF than IA produce (Appendix C). This indicates that having a strong positive attitude towards IA may not imply that IA produce is preferred to FF or GH produce. Results from subgroup WTP analysis reinforce this finding. When we considered only consumers with strong positive attitude towards consuming IA produce, we found WTP for IA was not higher than WTP for FF or GH.

Our results indicate that in terms of WTP, a niche market exists for IA produce among consumers who belong to the millennial cohort, live in urban areas, and identify male. Moreover, previous studies about consumer acceptance of new food technology often found that millennials, urban dwellers, and males are relatively receptive towards new food technology (Öz et al., 2018; Shaw & Mac Con Iomaire, 2019). It is especially promising for the future of both IA and urban communities that urban leafy green consumer WTP for IA is significantly higher than those of suburban or rural consumers. This is because policy makers and researchers have emphasized the potential impacts of IA in urban areas (Despommier, 2009; Pinstrup-Andersen, 2018; Research and Development Potentials in Indoor Agriculture and Sustainable Urban Ecosystems, 2019).

Future studies should investigate consumer WTP for leafy green attributes by focusing on attribute levels in a more tangible way. This paper intentionally avoids sharpening the level of attributes like freshness and taste in order to imitate the real choice situation, but it limits the interpretation of the results. For example, a one unit increase in taste is unquantifiable. In this case, an alternative way of investigating taste of leafy green preferences would involve conducting a taste panel experiment of leafy green consumers for controlled quality levels. Since our results indicate that taste and freshness of leafy greens can affect profitability of IA, detailed taste profiles and signals for freshness should be identified. Additional work could investigate the factors underlying the differences in WTP for leafy greens attributes across demographic subgroups. For example, our results indicate that millennials are willing to pay higher premia for IA compared to other generations, but it is important to understand why to effectively appeal to this cohort.

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APPENDIX A: TABLES AND FIGURES

Table 2.1 Statistical summary of the sample socio-demographics and of the U.S. population (%).

		Sample (n=2,114)	U.S. population[a]
Age	18 – 25 (18 – 24)[b]	15.61	11.90
	26 – 35 (25 – 34)	18.35	17.85
	36 – 55 (35 – 54)	31.88	32.43
	56 – 65 (55 – 64)	15.37	16.64
	66 – 80 (65 – 79)	17.27	16.19
	Over 81 (Over 80)	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	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 ($/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	79.61	80.7
	Rural	20.39	19.3

Notes: [a] U.S. population estimates were obtained from U.S. Census Bureau's 2019 American Community Survey.
[b] Age brackets used for U.S. population in parenthesis

Table 2.2 List of leafy green attributes and levels used for the choice experiment.

Attributes	Levels		
Alternative specific constants (ASC)	Indoor Agriculture (IA) grown	Greenhouse (GH) grown	Field Farm (FF) grown
Price[a]	\$2.9 / 4.5 oz.	\$2.9 / 4.5 oz.	\$1.9 / 4.5 oz.
	\$3.9 / 4.5 oz.	\$3.9 / 4.5 oz.	\$2.9 / 4.5 oz.
	\$4.9 / 4.5 oz.	\$4.9 / 4.5 oz.	
	\$5.9 / 4.5 oz.	\$5.9 / 4.5 oz.	
Freshness	OK	OK	OK
	Good	Good	Good
	Very good	Very good	Very good
Taste	OK	OK	OK
	Good	Good	Good
	Very good	Very good	Very good
Nutrient level	None	None	None
	20% more nutrient	20% more nutrient	20% more nutrient
	50% more nutrient	50% more nutrient	50% more nutrient
Food safety	None	None	None
	Food safety certified	Food safety certified	Food safety certified

Notes: [a] Commodity lettuce (FF grown) based on the retail price report by USDA in 2021 [32]. GH and IA-produced premium lettuce prices collected from select U.S.-based chain grocery stores' websites (e.g., Wholefoods, Meijer, Kroger, Aldi), in September 2020.

Table 2.3 Random parameter (RP) and latent class (LC) logit models estimated results.

	Random parameters (RP) model		Latent class (LC) model		
			Class1	Class2	Class3
	Mean (μ)	SD (σ)	"Quality seekers"	"Price conscious"	"Focused practicals"
Indoor Ag.	-0.434**	4.689***	0.433***	2.126***	-3.425***
	(0.183)	(0.182)	(0.167)	(0.441)	(0.313)
Greenhouse	-0.151	4.590***	0.610***	2.407***	-3.074***
	(0.179)	(0.180)	(0.164)	(0.430)	(0.307)
Field-farming	0.536***	4.518***	0.575***	3.579***	-2.701***
	(0.165)	(0.181)	(0.152)	(0.362)	(0.251)
Price	-0.317***	-[a]	-0.126***	-1.380***	-.573***
	(0.018)	- [a]	(0.018)	(0.131)	(0.064)
Taste	0.727***	0.724***	0.432***	0.671***	0.882***
	(0.031)	(0.035)	(0.022)	(0.090)	(0.058)
Freshness	0.719***	0.735***	0.443***	0.788***	0.879***
	(0.030)	(0.035)	(0.022)	(0.078)	(0.058)
Nutrient level	0.212***	0.447***	0.187***	0.558***	0.096*
	(0.025)	(0.060)	(0.021)	(0.075)	(0.054)
Food safety	0.248***	0.345***	0.178***	0.167***	0.171***
	(0.019)	(0.065)	(0.017)	(0.045)	(0.041)
Class probability	NA	NA	0.551	0.263	0.186
WTC[b]	NA	NA	1.103***	0.205	
			(0.182)	(0.213)	
McFadden Pseudo R-squared	0.266			0.258	

Notes: Standard errors in parentheses. Standard errors for estimates of parameters in RP are computed using the delta method.

[a] Price coefficient was treated as non-random parameter in RP.

[b] WTC is an indicator variable which equals to 1 if a respondent strongly agrees to consume leafy greens grown in IA farm, and 0 otherwise.

***, **, *: Significance at 1%, 5%, 10% level respectively.

Table 2.4 Mean willingness to pay (WTP) for attributes using full sample and latent classes.

	Full sample[a]	Class1[b] "Quality seekers"	Class2[b] "Price conscious"	Class3[b] "Focused practicals"
Indoor Ag.	-1.371**	3.807***	1.611***	-6.165***
	(0.614)	(0.839)	(0.168)	(0.873)
Greenhouse	-0.476	5.211***	1.731***	-5.522***
	(0.576)	(0.835)	(0.171)	(0.827)
Field-farming	1.690***	4.610***	2.480***	-4.828***
	(0.510)	(0.871)	(0.153)	(0.644)
Taste	2.295***	3.377***	0.438***	1.530***
	(0.16029)	(0.489)	(0.041)	(0.151)
Freshness	2.270***	3.461***	0.538***	1.527***
	(0.153)	(0.494)	(0.038)	(0.147)
Nutrient level	0.668***	1.417***	0.396***	0.201**
	(0.082)	(0.236)	(0.035)	(0.080)
Food safety	0.783***	1.467***	0.438***	0.224***
	(0.074)	(0.233)	(0.041)	(0.067)
Sample size	2,114	1,173	562	379
N	12,684	7,038	3,372	2,274

Notes: WTP estimates in $/4.5 oz. Standard errors in parentheses. Standard errors for estimates of WTP are computed using the Krinsky and Robb method.
[a] WTP of full sample (2,114) are estimated using RP model.
[b] Class specific WTP are estimated using LC model.
***, **, *: Significance at 1%, 5%, 10% level respectively.

Table 2.5 Model fit criterions.

Models (Sample size = 2,114)	Log-likelihood	AIC/N	BIC/N	AIC3/N
MNL	-14442.5	2.279	2.283	2.279
RP without correlated parameters	-13349.4	2.107	2.116	2.108
RP with correlated parameters	-12904.1	2.040	2.062	2.043
LC with 2 classes	-13658.1	2.156	2.167	2.158
LC with 3 classes	-13039.8	2.061	2.077	2.063
LC with 4 classes	-12759.2	2.018	2.040	2.021
LC with 5 classes	-12674.6	2.006	2.034	2.010

Table 2.6 Average elasticities over full sample with respect to attribute price.

In alternative	Choice Alternatives			
	IA	GH	FF	NB
Indoor Ag.	-0.931***	0.282***	0.150***	0.133***
	(0.003)	(0.001)	(0.001)	(0.001)
Greenhouse	0.334***	-0.870***	0.182***	0.173***
	(0.001)	(0.003)	(0.001)	(0.001)
Field-farming	0.256***	0.257***	-0.242***	0.231***
	(0.001)	(0.001)	(0.001)	(0.001)

Notes: Standard errors in parentheses. Standard errors for the estimates of elasticities are computed using the Krinsky and Robb method.
Elasticities of full sample (2,114) are estimated using RP model.
***, **, *: Significance at 1%, 5%, 10% level respectively.

Table 2.7 Average price direct elasticities across latent classes.

	Latent Classes[a]		
	Class1 "Quality seekers"	Class2 "Price conscious"	Class3 "Focused practicals"
Attribute:Price			
Indoor Ag.	-0.418***	-6.779***	-2.467***
	(0.002)	(0.033)	(.015)
Greenhouse	-0.390***	-6.690***	-2.399***
	(0.002)	(0.035)	(0.016)
Field-farming	-0.195***	-.499***	-.936***
	(0.001)	(0.008)	(0.009)
Sample size	1,173	562	379
N	7,038	3,372	2,274

Note*s:* Standard errors in parentheses. Standard errors for the estimates of elasticities are computed using the Krinsky and Robb method.
[a] Class specific elasticities are estimated using LC model.
***, **, *: Significance at 1%, 5%, 10% level respectively.

Figure 2.1 An example of choice task used in the choice experiment.

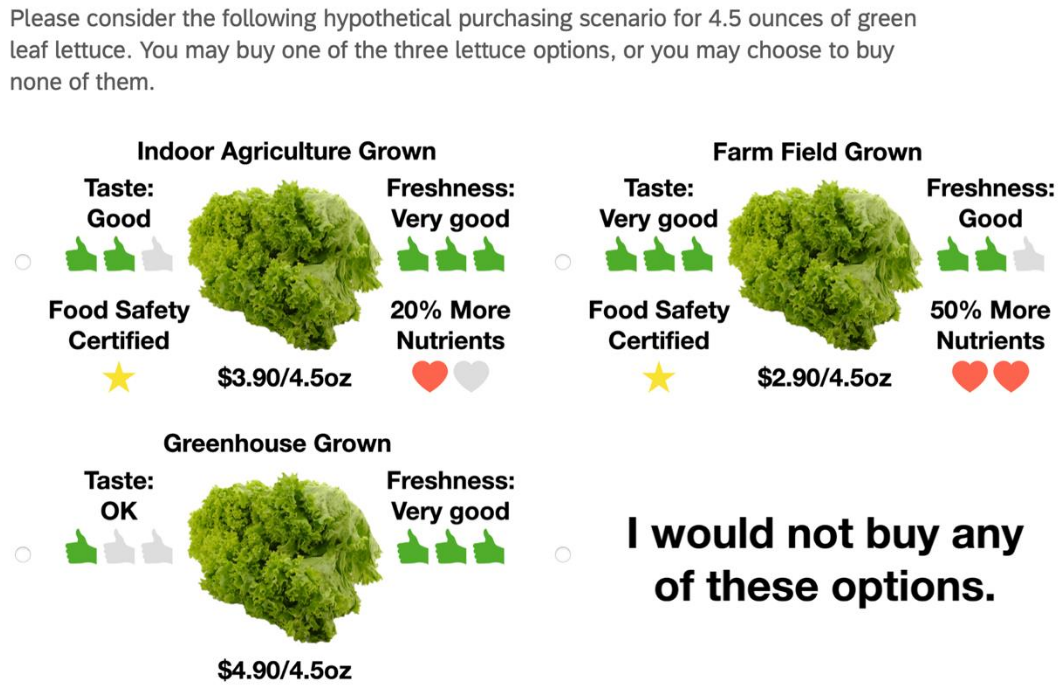


Figure 2.2 Images of each production method provided before the choice experiment.

The following questions will be referring to these three different **agricultural systems** used to grow leafy greens.

		
Field Farming	Greenhouse	Indoor Agriculture (IA)

Figure 2.3 Distribution of estimated individual willingness to pay (WTP) for attributes of leafy greens, across sample, including production systems (indoor agriculture (IA), greenhouse (GH), and field farm (FF)), and quality attributes (taste, freshness, nutrient level, and food safety).

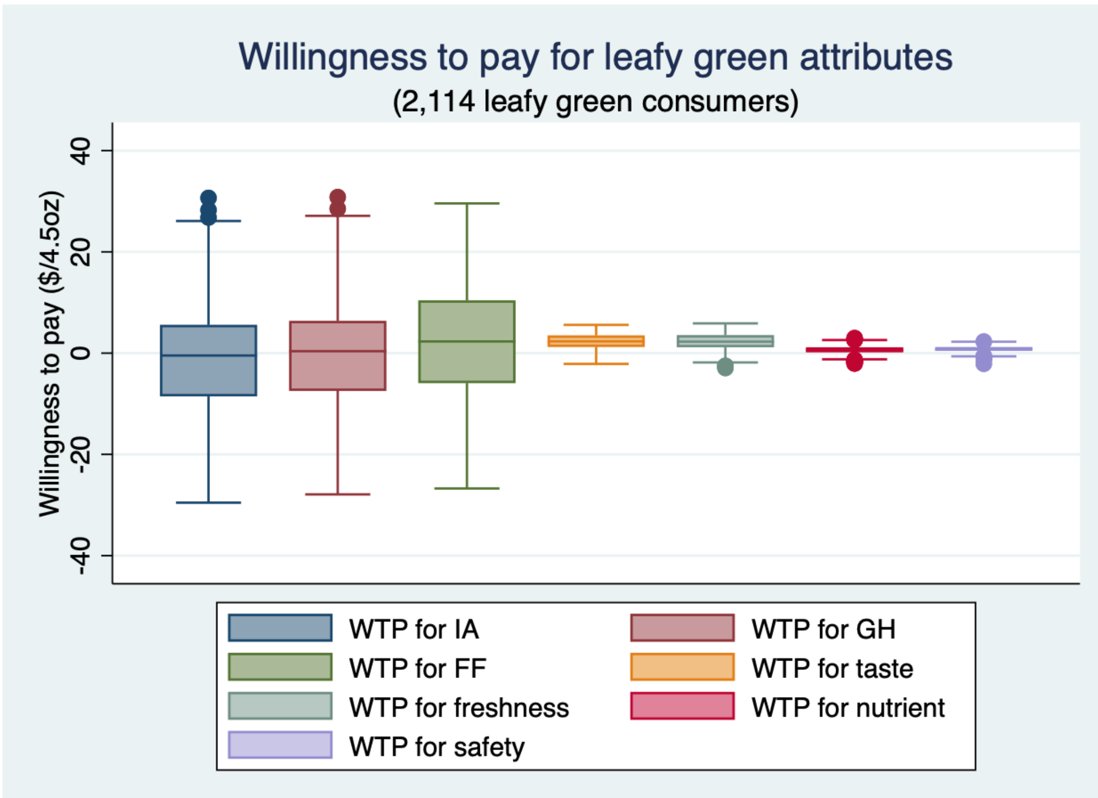


Figure 2.4 Mean willingness to pay (WTP) estimates ($/4.5oz) for IA lettuce across generations.

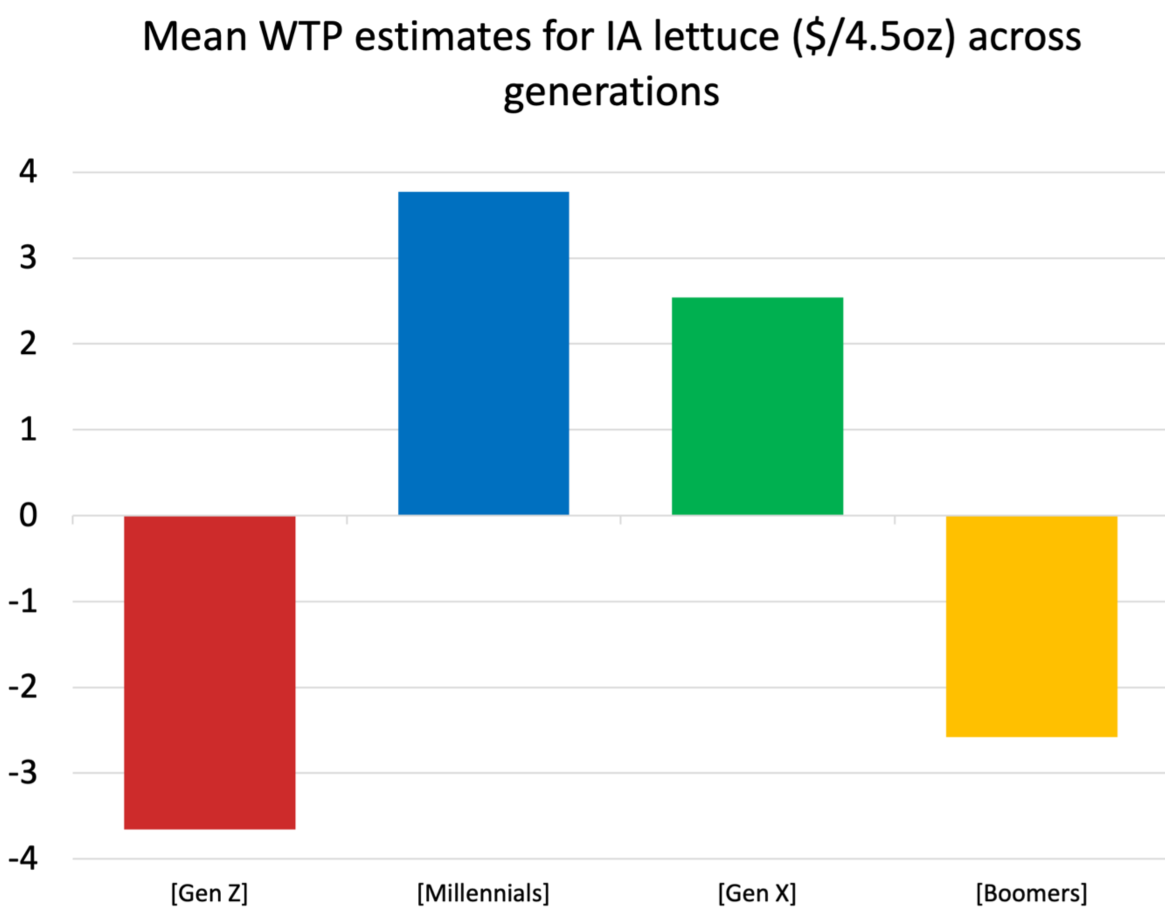
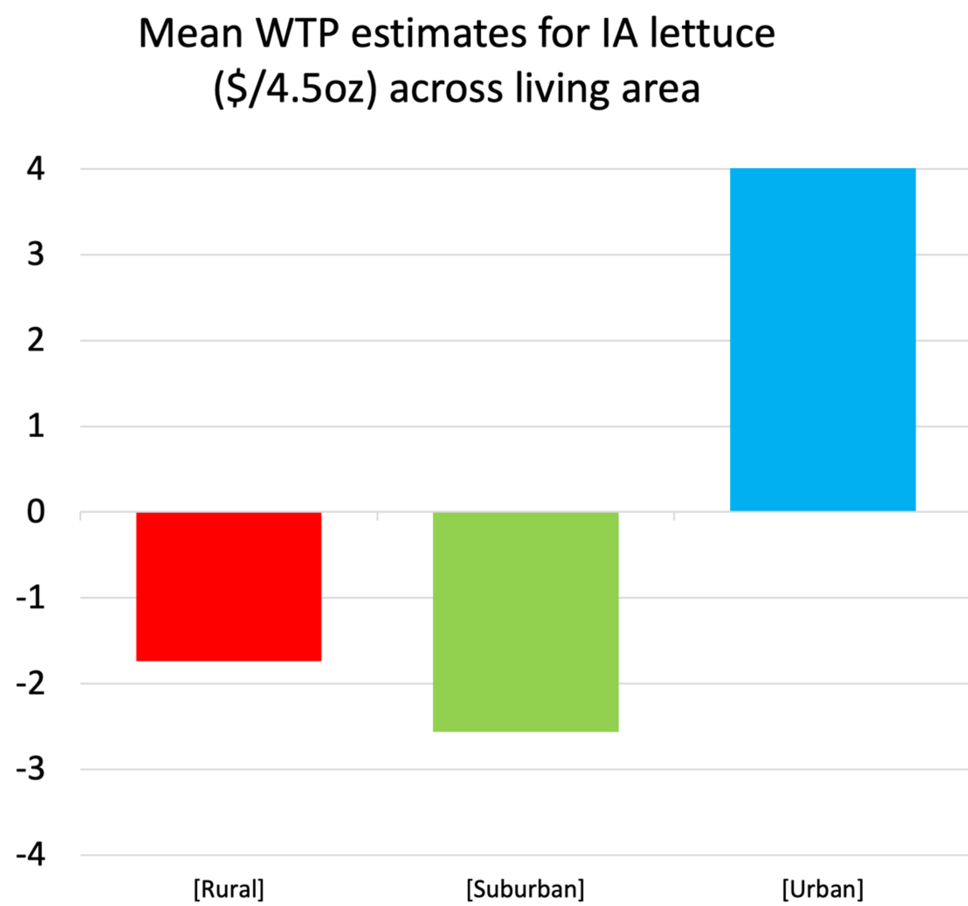


Figure 2.5 Mean willingness to pay (WTP) estimates ($/4.5oz) for IA lettuce across living area.



APPENDIX B: CHOLESKY MATRIX

Table 2.8 Estimation result of Cholesky matrix for the random parameters (RP) model.

Variable	IA	GH	FF	Taste	Freshness	Nutrient level	Food safety
IA	4.69***						
GH	-4.59***	0.04					
FF	-4.26***	0.43**	1.44***				
Taste	0.54***	-0.47***	-0.08	0.07			
Freshness	0.60***	-0.16***	0.08**	-0.28***	0.08		
Nutrient level	0.06	0.09	0.13***	0.17*	-0.20**	0.29***	
Food safety	0.10***	-0.02	0.02	0.12	-0.16*	-0.25***	0.31***

Notes: The standard errors for these estimators are computed using the delta method.
***, **, *: Significance at 1%, 5%, 10% level respectively.

Table 2.9 Estimation result of correlation matrix for the random parameters (RP) model.

Variable	IA	GH	FF	Taste	Freshnes s	Nutrient level	Food safety
IA	1						
GH	-.999	1					
FF	-.943	.944	1				
Taste	.746	-.752	-.798	1			
Freshness	.815	-.817	-.757	.703	1		
Nutrient level	.124	-.122	-.009	-.025	-.112	1	
Food safety	.286	-.286	-.252	.274	-.076	-.309	1

APPENDIX C: DEMOGRAPHICS ACROSS LATENT CLASS

Table 2.10 Demographics across Quality seekers, Price conscious, and Focused practicals (%).

		Quality seekers	Price conscious	Focused practicals
Generation	Gen Z	21.6	6.7	12.3
	Millennials	35.5	16.4	18.2
	Gen X	23.2	26.1	20.6
	Baby boomers	19.8	50.8	48.9
Gender	Male	54.1	38.3	32.9
Education	Less than high school degree	2.3	1.7	2.9
	High school graduate	23.0	26.0	23.2
	Some college	20.8	24.3	24.0
	Associate's degree	10.0	9.8	10.7
	Bachelor's degree	21.6	24.6	24.2
	Post graduate degree	22.3	13.7	15.0
Ethnicity	Hispanic	21.8	6.1	7.7
Marital Status	Married	49.9	56.3	43.6
Household size	1 person	17.9	20.7	24.2
	2 people	30.5	43.0	40.2
	3 people	19.9	18.2	16.7
	4 or more people	31.7	18.0	18.9
Household Income Quintile	1st quintile	26.1	22.4	28.1
	2nd quintile	17.1	23.6	21.5
	3rd quintile	16.2	18.4	15.7
	4th quintile	22.2	22.1	19.1
	5th quintile	18.3	13.5	15.5
Living area	Urban	40.4	20.2	20.8
	Suburban	43.2	53.0	57.1
	Rural	16.3	26.8	22.0

Notes: Generations defined by ages in 2021: Gen Z (18-25), Millennials (26-40), Gen X (41-55), Boomer (56 and over).

APPENDIX D: WILLINGNESS TO PAY ACROSS WILLINGNESS TO CONSUME

We investigate whether WTP for the attributes of leafy greens vary across our sample by estimating WTP for each subgroup of interest using the RP specification. As expected, WTP for IA production method was significantly higher among respondents who strongly agree to willingness to consume ($2.65/4.5oz) than the others (-$2.64/4.5oz) (Table D1). However, this group of respondents showed higher WTP for other production methods too, making the order of preference for three production methods unchanged in terms of mean WTP. This indicates that even the group of people who have strong positive attitude towards willingness to consume IA produce are not willing to pay a larger premium for IA produce than for GH or FF produce. It could be because the price premium for leafy greens has been established for over decades by conventional methods. Attitude towards IA yields significant difference in WTP for IA, but it appears those with positive attitudes toward IA do not favor this production technology compared to well-known GH and FF production methods.

Table 2.11 Mean willingness to pay (WTP) estimates ($/4.5oz) across willingness to consume (WTC) IA produce.

	Survey question: "I am willing to consume leafy greens grown in IA farm"	
	Non-strongly agree	Strongly agree
Indoor Ag.	-2.638***	2.654**
	(0.733)	(1.262)
Greenhouse	-1.855***	3.449***
	(0.694)	(1.259)
Field-farming	0.893	4.400***
	(0.566)	(1.237)
Taste	2.252***	2.535***
	(0.186)	(0.369)
Freshness	2.288***	2.325***
	(0.188)	(0.334)
Nutrient level	0.670***	0.736***
	(0.096)	(0.175)
Food safety	0.801***	0.730***
	(0.089)	(0.156)
Sample size	1,558	556
N	9,348	3,336

Notes: WTP values in $/4.5oz. Standard errors in parentheses. Standard errors for WTP estimates are computed using the Krinsky and Robb method. ***, **, *: Significance at 1%, 5%, 10% level respectively.

CHAPTER 3

CAN INDOOR AGRICULTURE FEED GROWING URBAN POPULATION WHILE ACHIEVING ECONOMIC SUSTAINABILITY AND ENERGY USE EFFICIENCY?

3.1 Introduction

The increasing urban population and the challenges associated with traditional agriculture have led to the exploration of alternative solutions to ensure sustainable food production. Indoor agriculture (IA) has emerged as a promising approach that holds the potential to address the food demand of urban areas while promoting sustainability (Armanda, Guinée, & Tukker, 2019; Despommier, 2009; Kozai & Niu, 2020; Pinstrup-Andersen, 2018). By utilizing controlled environments and innovative technologies, IA enables year-round cultivation of crops, minimizing the reliance on external factors such as climate and soil conditions. However, to fully harness the benefits of IA and maximize its potential, optimization of IA systems is crucial.

This study seeks to develop an optimization model for IA system that aims to achieve a balance between economic and environmental sustainability. By carefully designing and managing various components within the IA system, such as the production schedule, farm size, and farm location, it becomes possible to enhance both profitability and energy use efficiency. This study proposes a comprehensive optimization model for IA systems using a multi-objective optimization framework.

This is a first attempt to explore the sustainability of IA as a system optimization outcome, addressing a significant gap in the existing IA literature. The proposed optimization model integrates a production module, cost module, and revenue module to capture the intricate dynamics of IA systems in the context of urban areas. By integrating these modules, this framework aims to optimize both profit and energy use efficiency (EUE), which are crucial factors for the long-term success and viability of IA operations. While previous studies have examined these modules individually or partially, this study provides a comprehensive analysis of their interrelationships. For example, the production module has predominantly been explored by horticultural scientists who have focused on optimizing environmental variables to maximize yield or resource use efficiency (Bian, Yang, & Liu, 2015; Kelly, Choe, Meng, & Runkle, 2020; Meng, Boldt, & Runkle, 2020; Pennisi et al., 2019; Touliatos, Dodd, & McAinsh, 2016; Zhang, Whitman, & Runkle, 2019). On the other hand, the revenue module has been investigated primarily through consumer preference analysis, utilizing methods such as choice experiments or market analysis (Coyle & Ellison, 2017; Huang, 2019; Kurihara, Ishida, Suzuki, & Maruyama, 2014; Seong, Valle De Souza, & Peterson, 2023; Yano, Nakamura, Ishitsuka, & Maruyama, 2021). Various research efforts have been made to identify the profitability of IA by analyzing the cost structure of IA systems (Eaves & Eaves, 2018; C. F. Nicholson, Harbick, Gómez, & Mattson, 2020; Zhuang et al., 2022). However, thus far, it has been challenging to discover publicly available studies that attempt to optimize EUE and profitability while integrating production systems and production schedule with their associated costs, and potential revenue arising from consumer willingness to pay in a whole-system analysis of IA system. The significance of incorporating these factors into the evaluation of IA systems is recognized in the existing literature (Kozai & Niu, 2020; Charles F Nicholson, Harbick, Gómez, & Mattson, 2020; Pinstrup-Andersen, 2018; van Delden et al., 2021). The integration of this model into urban areas addresses urban demand and climate goals as pointed out by Engler & Krarti (2021). In this context, EUE can be particularly important for IA to be successfully integrated in urban areas.

The multiobjective optimization model for an IA system proposed here, henceforth referred to as IA-MOO, considers three decision variables: production schedule, farm size, and farm location, aiming to optimize both profitability and EUE. The production schedule has an impact on both EUE and profit since a longer plant growth cycle can demand higher total energy use per plant while increasing yield. Conversely, as the production schedule extends, larger plants necessitate lower plant density in the growing area, resulting in a trade-off between fewer but larger plants and a higher number of smaller plants for a fixed-size growing area. IA-MOO employs optimal planting density model developed by Shasteen et al. (2022) to define farm size based on the optimal trajectory of planting density with varying production schedules.

Size of the farm affects profitability in the IA system through both construction and technology investment requirements. IA-MOO employs a coefficient of economies of scale, estimated by Zhuang et al. (2022), to calculate the capital investment and operating fixed costs for constructing an IA farm considering alternative farm sizes. Zhuang et al. (2022) identified a general trend of economies of scale in the IA industry, providing coefficients to estimate the capital investment cost of constructing an IA farm with varying sizes. Additionally, IA-MOO investigates the optimal farm location in terms of proximity to urban centers, considering trade-offs among land cost, transportation cost, and a hyper-local premium. The revenue module introduces an endogenously determined potential price premium attached to IA crops produced within urban areas for the attribute "hyper-local".

Similar to the standard definition of EUE as the use of less energy to perform the same task or produce the same result (The Office of Energy Efficiency and Renewable Energy, 2023), this study considers EUE as the energy usage with the minimum impact on total operating costs and consequently profitability. EUE is measured as electric energy use in kWh per crop produced in kilogram. Given the energy-intensive nature of IA, optimization effort towards EUE can alleviate the strain on energy resource use and contribute to the economic feasibility of IA systems, particularly in urban areas by mitigating the high operational costs associated with energy consumption. Additionally, consumer attitudes towards IA systems are influenced by perceived sustainability (Jürkenbeck, Heumann, & Spiller, 2019). While it is recognized that EUE alone may not address the entirety of agricultural sustainability (Bockstaller, Girardin, & van der Werf, 1997; Jones, 1989), prioritizing EUE in IA systems is crucial for ensuring long-term sustainability and compatibility with urban settings. In urban areas, where resource constraints and environmental considerations are of utmost importance, focusing on EUE is essential to meet sustainability goals.

By shedding light on the complexities and trade-offs involved in optimizing IA systems, this study contributes to the existing literature on sustainable urban agriculture and supports the development of practical guidelines for the successful implementation of IA systems. The insights gained from this research have the potential to inform decision-making processes in the design and management of IA systems, ultimately advancing the goal of sustainable food production for urban populations.

3.2 Methodological Framework – IA-MOO

This paper presents a comprehensive optimization tool developed for IA systems by integrating production, revenue, and cost considerations, while simultaneously optimizing two objectives: profitability, measured as earnings before tax (EBT) and energy use efficiency (EUE). These objectives may potentially compete with each other at the optimal level. For example, the reduction of energy use per cycle by shortening the production schedule to enhance EUE may hinder plant growth causing smaller yield per plant. On the other hand, a profit-maximizing strategy that aims to improve revenue per cycle through the production of larger plants would maximize yield while requiring higher energy use per cycle. However, in some ranges of production schedule variable, it is possible to find solutions where both objectives can be improved simultaneously, resulting in Pareto improvement. This is because enhancing EUE would positively affect energy-related costs, resulting in an upward effect on profitability. The main objective of this model is to define the point at which energy used to enhance plant growth starts hindering profitability, resulting in trade-offs between the two objectives.

To identify non-dominated solutions (Pareto front) for this problem, this framework employs a multiobjective optimization (MOO) framework using the nondominated sorting in genetic algorithms-II (NSGA-II) developed by Deb (2001). MOO has been widely used in various fields, including optimal control in agricultural production systems that involve optimizing multiple objectives (Ramríez-Arias, Rodríguez, Guzmán, & Berenguel, 2012). Unlike calculus-based approaches, NSGA-II is a population-based method that searches for non-dominated solutions. In the NSGA-II algorithm, the solution population is iteratively updated by considering both non-domination ranking and the "crowding distance," which promotes diversity within the population. During this update process, crossover and mutation operations are applied to generate offspring solutions aiming to create a population of candidate solutions that converge towards the optimal solution. Consequently, NSGA-II effectively uncovers non-convex Pareto fronts that may be challenging for traditional calculus-based methods to handle (see Deb (2001) for more details). An R package “rmoo” was used to implement NSGA-II algorithm. The program code used to generate solutions is available from the author upon request.

The IA-MOO comprises three modules: revenue, cost, and production. The framework is designed to optimize two objectives, EBT and EUE, while considering three decision variables: production schedule, a base unit size, and the distance to the urban center (Fig. 3.1). Defined as the number of days crops are grown from transplant to harvest, the production schedule is a crucial variable that governs the production of fresh produce in IA systems. It not only determines yield and harvest frequency through the maturity of the crop but also influences fixed and variable operating costs. An optimal planting density model developed by Shasteen et al. (2022) was used to predict the plant head-mass and optimal planting density based on the production schedule. The base unit size refers to the unit size of the propagation stage, which acts as a multiplier for the total growing area of the IA farm. Additionally, the distance to the urban center is considered as another decision variable, introducing trade-off between revenue and cost into the model. This variable provides insights into the ideal location of the farm in relation to metropolitan areas.

It is crucial to highlight that IA-MOO is specifically designed to optimize the IA system by integrating the three modules, taking into account the interactions among the decision variables. These interactions are reflected as trade-off relationships in relation to the objectives. The following subsections offer a detailed description of the relationships among the decision variables and outline the background assumptions for each module.

3.2.1 Revenue module - Price premium of IA lettuce

IA produce has the potential to command price premiums due to the unique characteristics of the IA production system. For instance, IA systems can emphasize significantly higher water use efficiency compared to conventional agricultural production systems (Stein, 2021), which is recognized as a major agri-food credence attribute by producers, retailers, and consumers (Schrobback, Zhang, Loechel, Ricketts, & Ingham, 2023). Additionally, when the IA system is ideally designed, it can effectively adjust quality attributes such as taste, crunchiness, or nutrient levels by exerting complete control over the environmental variables that influence crop growth.

These distinctive capabilities of the IA system differentiate it from conventional methods and have the potential to attract price premiums from consumers seeking high-quality leafy greens.

Another opportunity to obtain price premiums for indoor agriculture (IA) produce lies in leveraging its relatively small footprint area requirement for the same output and by approaching urban consumers more closely. In line with the expectations of urban agriculture (Mougeot, 2000), the potential of IA to offer urban populations fresher produce from urban or suburban areas has generated excitement among IA researchers, policymakers, and stakeholders since the concept of IA was introduced (Al-Kodmany, 2020; Despommier, 2009; Dimitri, Oberholtzer, & Pressman, 2016; Jacobs-Young, 2019; Charles F Nicholson et al., 2020).

The revenue-generating potential of IA has been extensively discussed and acknowledged (Despommier, 2013; Eaves & Eaves, 2018; Valle de Souza, Peterson, & Seong, 2022). However, there has been limited attempt in the IA profitability literature to model premium prices based on the potential of IA. Charles F Nicholson et al. (2020) conducted a comparison of the profitability of IA operations at different distances from urban wholesale markets, but their study made an assumption of a fixed price, despite being aware of the potential variations in prices due to local premiums. Similarly, Eaves & Eaves (2018) compared the profitability of greenhouse and IA operations while assuming the same price for lettuce grown by either a greenhouse or an IA farm, but they did acknowledge the additional resource use efficiency of IA systems in relation to greenhouses, which could hold significant value for growers.

In contrast to previous studies, this research proposes a price model for IA produce that incorporates consumer willingness to pay (WTP) for IA-produced lettuce and an additional hyper-local premium. Firstly, an initial base price for IA-produced crops is taken from previous consumer research. This study uses WTP for IA lettuce among urban leafy green consumers in

U.S., as estimated by Seong et al. (2023). This paper assumes a 10% of premium for the hyper-local attribute based on previous findings on local premium and demand for local agri-food products (Table 3.1) (Carpio & Isengildina-Massa, 2009; Enthoven & Van den Broeck, 2021; Solarz, Raftowicz, Kachniarz, & Dradrach, 2023; Willis, Carpio, & Boys, 2016). A 50% of retail margin is assumed following consultation with industry stakeholders. Considering the New York City metropolitan area, the radius of urban circle and suburban circle is assumed to be 30km and 60km, respectively. For this example, a hyper-local distance of 15km was adopted.

The model then endogenously determines the price of the produce, considering the distance between the farm and urban consumers. The hyper-local area is defined by the geographical proximity between IA growers and consumers. Although a commonly agreed-upon definition of the term "local" in relation to locally grown food does not exist, it can be conceptualized for consumers in terms of the distance measured in miles (Durham et al., 2009; Paciarotti & Torregiani, 2021). For example, Durham et al. (2009) found that consumers' perception of "local" for fresh produce tends to strengthen as the geographical proximity, defined in miles, increases. Previous literature on willingness to pay (WTP) for local fresh produce, short food supply chains (SFSC), and demand for local agri-food products (Carpio & Isengildina-Massa, 2009; Enthoven & Van den Broeck, 2021; Solarz et al., 2023; Willis et al., 2016) supports the assumption of the presence of a hyper-local premium. While the definition of local foods may vary in the scientific literature, empirical studies have found a willingness to pay a premium for the local attribute. Assuming that the willingness to pay for the hyper-local attribute will be no less than the willingness to pay for the local attribute, this study considers the willingness to pay a premium for local produce estimated by Carpio & Isengildina-Massa (2009) as an upper bound for the willingness to pay a premium for hyper-local produce.

Therefore, this paper considers two sources of price premiums for IA-grown lettuce: the first source is that the lettuce was cultivated in an IA farm, and the second source is that the lettuce was grown within a hyper-local distance. Furthermore, we focus on urban consumers as the sole target group. This choice not only makes the model more manageable but also aligns with the main focus of this study, which is to examine economic feasibility of sustainable IA farm operation near or within urban areas. As IA produce is the only produce that is considered in this analysis, the first source of premium is assumed as a given baseline. As for the second source of premium, it can be modeled as a function of the distance between the farm and urban consumers.

Both the urban area and the hyper-local area are assumed to be circular shape, and urban consumers are assumed to be uniformly distributed within the urban area. The proportion of urban consumers living within the hyper-local area of a farm in relation to the total number of urban consumers is estimated by calculating the overlapping areas of the two circles. This ratio is assumed to be the share of sales for the hyper-local premium, as it represents the share of consumers within the hyper-local distance. Although this approach has some limitations, it enables to incorporate the endogenously determined price premium of IA within the model.

Based on these spatial assumptions, a price model for lettuce is formulated to incorporate the two aforementioned sources of potential price premium for IA produce. The introduction of a hyper-local premium creates an incentive to farmers to increase their revenue as they move closer to the urban center. Additionally, the transportation cost will also influence profitability as it changes in the same direction as the distance to the urban center. On the other hand, there will be trade-offs in terms of land cost, as urban areas typically have higher land prices compared to suburban and rural areas.

3.2.2 Cost module

The primary challenge of locating an IA farm close to urban dwellings is the high cost of land. While IA offers the advantage of maximizing production within a significantly smaller land area in relation to field or greenhouse systems as it utilizes the vertical space, the expensive land costs in urban areas can still pose a barrier to IA farms. To address this trade-off, three different land cost scenarios were considered, namely urban, suburban, and rural areas, with urban land being the most expensive. This approach will impose a penalty on the profitability of IA farms as they move closer to the urban center.

To model the total land requirement, an economically optimal space decision model for IA operations, described in Shasteen et al. (2022), was utilized. Their research demonstrated that the optimal farm size can be determined by integrating horticulture engineering experimental results, considering space and time constraints. By using the experimental findings on optimal environmental control for lettuce production to maximize yield, they established a relationship between the required size of the total growing space and the production schedule. Building on that work, the total growing area requirement becomes a function of the production schedule and the unit area needed for the propagation stage. Subsequently, the total land area requirement based on the total growing area requirement is estimated.

The total floor area of the growing area was obtained by dividing the total growing area for each stage by the number of shelves and adding the proportional corridor area (Uraisami, 2022). This production structure is designed with eight shelves in the propagation stage and four shelves in the production stage. Since the plant is relatively shorter during its younger stage, it can be assumed that the growing shelves are stacked with 8 tiers in the propagation stage, while the production stage uses only 4 tiers. Proportional space requirements for the growing structure, buffer space, storage, packaging, office space, and parking were included in the calculation of the total land area required following the approach of Eaves & Eaves (2018).

To account for capital investment costs, a coefficient of economies of scale is applied into the model based on estimates from Zhuang et al. (2022). Their study utilized data from the US, EU, Japan, Canada, and China to estimate economies of scale in the capital investment required for constructing an IA farm. By employing the empirical method developed by Haldi & Whitcomb (1967), they demonstrated the existence and estimated a general trend of economies of scale in the IA industry. Based on the findings of Zhuang et al. (2022), the total capital investment required to build an IA farm and equip it with advanced technology is modeled as a function of the total growing area of the farm. Furthermore, since they cover a range of data spanning from small-size farms (12 m^2 of total growing area) to large-size farms (100,000 m^2 of total growing area), there is no need for extrapolation within this range to estimate the capital investment cost.

For the land price, New York City metropolitan area is chosen as an example, and a land value assumed by Charles F Nicholson et al. (2020) is used so that the result can be comparable (Table 3.2). Since Charles F Nicholson et al. (2020) chose the location of a hypothetical IA farm close to wholesale market in the New York City metropolitan area, the assumption aligns with the current model. For the land price of suburban and rural area, this paper hypothesizes a 50% decrease from the urban area and suburban area, respectively.

The annual cost of investing in IA, assumed that both the total investment for constructing the IA farm and the total cost of the land would be financed through a ten-year loan with an annual interest rate of 6.2%. This assumption aligns with the approach taken by Charles F Nicholson et al. (2020). A mortgage-style amortization method is employed, which is applicable in our case as it calculates a constant monthly payment to fully repay the loan. The maintenance and depreciation costs for buildings and technological equipment are calculated based on a proportion of the total investment cost for building and technology. In accordance with Zhuang et al. (2022), an annual maintenance rate of 1.5% and a lifespan of 15 years for these assets' depreciation is considered.

Variable operational costs were estimated based on the unit size of the growing area, following the approach of Shasteen et al. (2022), with the exception of transportation costs. The costs of electricity, labor, seeds, substrates, and packaging were calculated per square meter of the growing area, making it easily applicable to the current IA-MOO model, which requires cost information that can accommodate variations in farm size.

For the estimation of seed prices, this study employed a power function to incorporate economies of scale. After consulting with experts in the seed industry about volume pricing strategies and common growers' practice, it is assumed that this hypothetical IA farm uses pelleted seeds, which are delivered on a monthly basis through a yearly contract. The price of seeds is determined based on the annual quantity of seeds required. Since the price of seeds decreases with larger quantities due to bulk discounts, a power function is incorporated into the model to estimate the price of pelleted seeds as a function of the quantity.

Regarding logistics, the concept of a short food supply chain (SFSC) was adopted, which is characterized by a limited number of intermediaries or the absence of intermediaries, along with geographical proximity between producers and consumers (Paciarotti & Torregiani, 2021). Transportation costs were then estimated by assuming a short food supply chain with a single intermediary, a wholesale market located in the urban center. This assumption simplifies the logistics and makes the model more manageable for modeling purposes. It is assumed that fresh produce is transported using a tractor-trailer powered by diesel fuel, with a maximum capacity of 900 cartons of lettuce, each containing 35lbs. This paper considered a fuel efficiency of 3 km per liter, following the approach of Charles F Nicholson et al. (2020). The average motor carrier cost per mile provided by the National Private Truck Council (2021) is applied.

It is worth noting that, although beyond the scope of this paper, when the IA farm is located within the hyper-local distance, IA produce can be directly sold to consumers using specialized logistics tailored for short distances, such as drone delivery, as discussed in the literature (Durand & Gonzalez-Féliu, 2012; Pachayappan & Sundarakani, 2022; Suryawanshi, Dutta, L, & G, 2021).

3.2.3 Production module – Daily harvest, Optimal density, Optimal space and time model

With a focus on optimization of lettuce production in an IA setting, the optimal planting density model developed by Shasteen et al. (2022) was used. For the lettuce variety, a mixed variety was used, consisting of a 50:50 blend of butterhead 'Pascal' and 'Seurat'. The optimal planting density plays a crucial role in profitability as it allows for minimal space usage while maximizing yield. Shasteen et al. (2022) determined the optimal planting density for lettuce growth in an IA setting by combining information on the projected canopy area and employing a hexagon tiling algorithm. Based on plant growth parameters estimated by Shasteen et al. (2022), optimal density and associated plant head-mass can be estimated as a function of production schedule, which is the amount of time to grow plant. In this study, the production schedule (Table 3.3) is defined as the number of days from transplant to harvest. This definition is based on the assumption that transplanting occurs only once during the plant growth cycle, and the number of days before transplant remains constant. Consequently, the variable that determines the production schedule in our assumption is the number of days after transplant, henceforth referred to as DAT. The predictive model provides optimal planting density, predicted head mass, and space requirements for both propagation stage and production stage. Although omitted for conciseness, detailed environmental setpoints for lettuce growth in this model such as CO_2, VPD, EC, and pH can be found in Shasteen et al. (2022).

Secondly, this paper expands the partial budgeting model first introduced in Shasteen et al. (2022), which incorporated the optimal planting density model and operational cost information, to investigate profitability of a simulated IA farm with a fixed size. The crucial advantage of this model is that since they estimated every cost component based on the unit size of the farm (1 m^2 of the propagation stage), making it useful when investigating different scales. It is also important to note that the economic analysis presented in Shasteen et al. (2022) also included the constraint of a daily harvest faced by a commercial farmer. One of the key advantages of an IA system is that it enables growers to produce plants in a manner similar to manufacturing goods in a factory. Considering the perishable nature of fresh produce, a daily harvest approach can enhance consistency and maintain high quality. Although rarely mentioned in the literature, the daily harvest constraint is crucial for the dynamic optimization of the entire IA system to efficiently utilize resources on an annual basis.

Based on these production and partial budgeting models, this paper defines lettuce production as a function of two inputs: DAT and base unit size of the propagation stage.

3.2.4 Mathematical representation of IA-MOO

The general form IA-MOO problem is represented as:

$$\max f_m(x)\,, m = 1,2 \tag{3.1}$$

$$\begin{gathered} \text{s.t.}\ 10 < TGA(x_1,x_2) < 100{,}000 \\ 7 < x_1 < 28 \end{gathered} \tag{3.2}$$

$$3 < x_3 < 100$$

$f_1(x)$ and $f_2(x)$ represent the two objective functions, EBT and EUE, respectively. A solution x is a vector of 3 real-valued decision variables: $x = (x_1, x_2, x_3)$, where x_1 represents the length of the production schedule (DAT) in days, x_2 represents the base unit size of the propagation stage in m^2, and x_3 represents the distance between the farm and urban center in km. The final two constraints consist of boundary values for variables, which limit each decision variable to assume a value between a minimum and maximum bound. Since this study is focused on investigating the location of the farm within a metropolitan area, the range of distance to urban center is limited to 100 km. A lower bound of 3 km on the distance is further imposed to prevent the scenario where the location of the farm coincides with that of the wholesale market, resulting in the degeneration of transportation costs. $TGA(x_1, x_2)$ represents a function for the total growing area, which will directly impact the total investment cost for building and technology of the IA farm using economies of scale parameters. Since these parameters were estimated based on the data from a certain range (Zhuang et al., 2022), a constraint is added to avoid extrapolating total investment cost estimation. It is important to note that constraints of total growing area and DAT will provide minimum and maximum bounds of the base unit size of the propagation area because the total growing area is a function of DAT and the base unit size.

3.2.4.1 Maximization of EBT

Profitability, measure as earnings before taxes (EBT) on an annual basis, is represented in the model by f_1, which is a function of annual revenue ($Revenue$) and total annual cost, including fixed costs (FC) and variable costs (VC):

$$f_1 = Revenue - (FC + VC) \tag{3.3}$$

3.2.4.2 Revenue

To estimate revenue, it is assumed that there are two potential sources of price premium. One is that IA produce can attract price premium due to being grown in an IA farm. The other is the additional opportunity of obtaining a hyper-local attribute if the farm is located very close to consumers. Total revenue becomes:

$$Revenue = Y * (P_{IA} + \theta(x_3) * P_{hl})\ where\ \theta \in [0,1] \tag{3.4}$$

where Y is the total annual yield in grams, and P_{IA} is the price premium that urban buyers are willing to pay for IA produce. P_{hl} is the additional price premium that urban buyers would be willing to pay based on the hyper-local attribute. θ is the fraction of buyers who would have additional willingness to pay based on hyper-local attribute. If a farm is located closer to urban center, θ will be closer to 1 because the farm is close to more potential buyers. If the urban area is completely inside the farm's hyper-local area, then every potential buyer would have the willingness to pay for the hyper-local attribute, resulting in $\theta = 1$. This paper defines θ as a function of the distance between the farm and the urban center, x_3, given the radius of the urban area (r_1) and the farm's hyper-local distance (r). θ is determined by calculating the intersection between two circles: the urban area and the farm's hyper-local area. There are four cases to consider the value of θ. Firstly, θ is 0 if two areas are not overlapping:

$$\theta = 0\ if\ x_3 \geq r_1 + r \tag{3.5}$$

If the distance between the farm and the urban center is greater than the sum of r_1 and r, there will be no consumers from the farm's hyper-local area. That is, if the farm is located too far away from the urban center, its produce cannot attain a hyper-local premium from any urban buyers.

Secondly, $\theta = 1$ if the farm's hyper-local area contains the urban area:

$$\theta = 1\ if\ 0 < x_3 \leq r - r_1 \tag{3.6}$$

In this case, the farm is not only located in close proximity to the urban center, but the hyper-local area is also larger than the urban area, generating additional revenue from all urban consumers.

Thirdly, if the farm's hyper-local area is smaller than the urban area, then the maximum value of θ would not be 1 but rather the fraction of the farm's hyper-local area over the urban area.

$$\theta = \frac{\pi r^2}{\pi {r_1}^2} \; if \; 0 < x_3 \leq r_1 - r \tag{3.7}$$

This is the case where the urban area contains the hyper-local area.

Lastly, if the urban area and the hyper-local area create intersect but do not completely overlap, θ will have the following values:

$$\theta = \frac{intersection}{\pi {r_1}^2} \; if \; |r_1 - r| < x_3 < r_1 + r \tag{3.8}$$

Where the $intersection$ is the area of overlap between the urban area and the hyper-local area. In this case, the fraction of consumer who would be willing to pay a hyper-local premium will be a value between 0 and 1.

3.2.4.3 Predictive production model for IA farm

$$Y = DH(x_1, x_2) * year \tag{3.9}$$

Y, the annual yield, is calculated as the daily harvest (DH) multiplied by a constant number 360, representing the number of days in a year. DH is a function of DAT and the base unit size of the propagation stage:

$$DH(x_1, x_2) = x_2 * DenBT * Headmass(x_1) \tag{3.10}$$

$Headmass(x_1)$ represents the head mass of each lettuce head in grams, and $DenBT$ is the density of crops in the propagation stage, represented by a constant number (1,550 heads/m^2).

3.2.4.4 Total annual costs

The estimation of annual *fixed costs (FC)* includes capital depreciation, maintenance, and mortgage payments for building, technology, and land:

$$FC = K * \left[\frac{1}{LS} + \delta\right] + pmt(K + L * P_L) * 12 \tag{3.11}$$

where K represents the capital investment cost of building and technology, L represents the total land area required, LS represents the life span of building and technology, δ represents maintenance costs of building and technology, and P_L represents the price of land in US dollars per square meter (\$/m^2). The monthly mortgage payment is calculated using the function $pmt(\cdot)$, which applies the annual interest rate and term. Both K and L are functions of the total growing area:

$$K = a_{capital} * TGA(x_1, x_2)^{b_{capital}} \tag{3.12}$$

$$L = FTGA(x_1, x_2) * Corrid * Facility * Additional \tag{3.13}$$

Using the economies of scale parameters, $a_{capital}$ and $b_{capital}$, estimated by Zhuang et al. (2022), K can be written as a function of the total growing area (TGA). L represents the footprint of the total growing area ($FTGA$) augmented by space for corridors, facility, and additional space for buffer, storage, packaging, office space, and parking.

$$\begin{aligned} TGA(x_1, x_2) &= (x_2 * DBT) + \left(x_2 * \left(\frac{DenBT}{DenAT(x_1)}\right) * x_1\right) \\ &= Sp_{propagation} + Sp_{production} \end{aligned} \tag{3.14}$$

$$FTGA(x_1, x_2) = \left(\frac{x_2 * DBT}{ShelfProp}\right) + \left(\frac{x_2 * \left(\frac{DenBT}{DenAT(x_1)}\right) * x_1}{ShelfProd}\right) \tag{3.15}$$

Both TGA and $FTGA$ include the area dedicated to the propagation stage and production stage. Sp_s represents the total space used per day in stage *s* (either propagation or production).

TGA is larger than $FTGA$ because the number of shelf tiers augments the total space for growing plants. In other words, footprint space can be saved by vertically stacking the growing beds. *ShelfProp* and *ShelfProd* are the number of shelf tiers in the propagation stage and production stage, respectively. It is important to note that daily harvest condition augments space requirement. Additional space is needed daily until empty space is made from harvesting so that the empty space can be reoccupied. Accordingly, the number of growing units in the propagation stage that are needed for daily harvest is defined by the number of days before transplant, DBT. The size of each growing unit is determined by the decision variable x_2, which is the multiplier of the area. Similarly, the number of growing units in the production stage that are needed for daily harvest is defined by x_1 (days after transplant). The size of each unit is determined by the base unit size (x_2) multiplied by the ratio of density before transplant (*DenBT*) to the density after transplant (*DenAT*).

Annual *variable costs (VC)* consist of four operational costs:

$$VC = ATC + AEC + ALC + ACC \tag{3.16}$$

Where annual transportation cost *(ATC)*, annual electricity cost (*AEC)*, annual labor cost (*ALC)*, and annual consumables cost (*ACC)* represent the respective costs.

ATC is estimated under the assumption of a short food supply chain with only one intermediary between producers and consumers. In this scenario, IA growers sell their produce to a wholesale market in the urban center, and growers transport their produce daily to the wholesale market using trucks and hiring drivers.

$$ATC = \left(1 + round\left(\frac{DH(x_1, x_2)}{TrCap}\right)\right) * 2 * x_3 * (P_{amcc} + P_d) * year \tag{3.17}$$

where p_d is the diesel cost using a tractor-trailer for 1km, and p_{amcc} is the average motor carrier cost for 1 km. The diesel cost is estimated based on transportation assumption (Nicholson et al., 2020). The average motor carrier cost includes maintenance, truck insurance, license, wages, benefits, and administration (National Private Truck Council, 2021). The function *round*(·) computes the rounding of the daily harvest divided by the capacity of the tractor-trailer (*TrCap*) so that the number of tractor-trailer required can be a whole number.

AEC is estimated as:

$$AEC = HV * \sum_{s} DEC_s * year, \qquad where\ s \in \{Propogation, Production\} \tag{3.18}$$

where HV represents the multiplier for HVAC loading (heating, ventilation, and air conditioning). DEC_s denotes the daily electricity costs for stage s:

$$DEC_s = DECsqm_s * Sp_s \tag{3.19}$$

$DECsqm_s$ represents the daily electricity costs for stage s per m^2. Sp_s denotes the total m^2 used in stage s on a daily basis.

$$DECsqm_s = \frac{\frac{DLI_s * 1{,}000{,}000}{\eta PAR}}{3{,}600{,}000} * p_e \tag{3.20}$$

DLI_s represents daily light integral, or total photons of photosynthetically active radiation per day received per m^2 area (mol/m^2·d) for stage s. ηPAR is the lighting efficacy (µmol /J), and p_e is the energy rate (\$/kWh).

$$DLI_s = \frac{(PhPer_s * 3600) * PPFD_s}{1{,}000{,}000} \tag{3.21}$$

$PhPer_s$ represents the photoperiod, or the number of hours the plants receive light in stage s, and $PPFD_s$ is the light intensity, defined as the photosynthetic photon flux density (µmol/m^2·s) for stage s. PPFD is higher during the production stage compared to the propagation stage. This means that a relatively lower energy level is considered optimal for the growth of lettuce at its younger stage.

ALC is estimated as the annual cost of wages:

$$ALC = DW * year \tag{3.22}$$

where DW represents daily labor cost, which is calculated as a function of hourly wage (w_h), benefit loading (w_b), and total labor hours per day (L_d):

$$DW = L_d\left(w_h * (1 + w_b)\right) \tag{3.23}$$

Following Shasteen et al. (2022), we consider five categories of labor: seeding (L_s), transplanting (L_t), harvesting (L_h), packaging (L_p), and cleaning (L_c). Seeding is conducted in the propagation stage, while transplanting, harvesting, and packaging are conducted in the production stage. Cleaning is performed in both stages and throughout the entire farm space, Sp, which includes both $Sp_{propagation}$ and $Sp_{production}$. The proportion of labor for each category is based on Kozai (2018). Defining the unit of L_s, L_t, L_h, L_p, and L_c as the proportion of labor hours per day and per m^2, L_d can be written as a function of the five categories of labor and the daily total space requiring labor:

$$L_d = L_s * x_2 + \left(L_t + L_h + L_p\right) * x_2 * \left(\frac{DenBT}{DenAT(x_1)}\right) + L_c * Sp \tag{3.24}$$

It is important to note that seeding occurs in one unit (x_2) of growing space in the propagation stage, while transplanting, harvesting and packaging occur in one unit of growing space in the production stage, estimated with $x_2 * \left(\frac{DenBT}{DenAT\,(x_1)}\right)$.

ACC is the sum of annual costs of seeds (AS), substrates (AM), and packaging (AP):

$$ACC = AS + AM + AP \tag{3.25}$$

Lettuce seeds used in industrial agriculture are primed and pelleted for quicker germination and seedling uniformity. After consulting with experts in the seed industry, the hypothetical IA farm in this paper is assumed to utilize pelleted seeds, which are delivered monthly through a yearly contract. The price of these seeds is determined by the yearly required quantity. To account for bulk discounts where the price decreases with larger quantities, a power function was employed to predict price of the seeds based on the quantity required. Publicly available data from a commercial distributer, Johnny's Selected Seeds, were used for this estimation.

$$P_s = a_{seeds} * nseeds_{annual}{}^{b_{seeds}} \tag{3.26}$$

nseeds represents the annually required quantity of seeds which is determined within the model.

$$nseeds_{annual} = x_2 * DenBT * year \tag{3.27}$$

Annual cost of seeds (AS) is as follows:

$$AS = P_s * nseeds_{annual} \tag{3.28}$$

As for the substrate, this study considered using 1-inch rockwool hydroponic grow cube starters, and the number of substrates required annually is the same as the number of seeds (*nseeds*). Price of substrate reflects average market prices collected on an online search.

$$AM = P_m * x_2 * DenBT * year \tag{3.29}$$

For packaging, this study opted for 4.5oz (=127.573 g) packaging, as the WTP for IA produce in this study was estimated based on this specific packaging size.

$$AP = P_p * \frac{DH(x_1, x_2)}{127.573} * year \tag{3.30}$$

3.2.4.5 Optimization of EUE

This paper defines energy use efficiency (EUE) as follows:

$$f_2 = \frac{HV * \sum_s DEC_s}{DH(x_1, x_2)/1000}, \qquad where\ s \in \{Propagation, Production\} \tag{3.31}$$

In other words, EUE is defined as the total electricity use for lighting and HVAC per total kilograms of lettuce produced per day. Since EUE is measured in kWh/kg, optimizing EUE is done by minimizing f_2, ensuring that less energy is used to produce 1 kg of lettuce.

3.3 Result and Discussion - An example Pareto fronts of IA-MOO with constraints on growing area size

The final population generated by solution search algorithm, NSGA-II, for the IA-MOO problem consists of non-dominated solutions forming Pareto front. In Figure 3.2, four panels - A, B, C, and D - represent the four Pareto front results from solving the IA-MOO problem with four varying constraints on the upper bound of the total growing area: 100 m^2, 800 m^2, 2000 m^2, and 100,000 m^2. The corresponding results are reported in Table 3.4. The Pareto front shows that two objectives are conflicting within a certain range. Moving in the southeast direction represents a way to improve EUE and EBT, making it the path to Pareto improvement. Taking the 100 m^2 constraint as an example, one extreme solution combination of EUE and EBT is 11.20 kWh/kg and \$5,000/annum, while the other extreme is 11.23 kWh/kg and \$5,300/annum. These are non-dominant solutions, because an EUE of 11.20 kWh/kg is better than 11.23 kWh/kg, but an EBT of \$5,300/annum is better than \$5,000/annum.

In Table 3.4, as the constraint on the growing area is relaxed, EBT improves while EUE remains the same. It is essential to note that even with the relaxation of the constraint, the range of solution DAT remains constant, but the base unit size varies. Furthermore, it should be observed that solutions are determined at the maximum allowed size of the total growing area. This implies that profit improves as the farm capacity increases, but EUE is not affected. Combining these factors together, it can be inferred that making the most out of economies of scale is crucial for maximizing profit. As the scale increases, both land costs and operational costs increase. However, the unit investment cost of building and technology decreases due to economies of scale (as shown in Table 3.5), resulting in improved profitability along with increased revenue.

To achieve the maximum allowed total growing area, DAT and base unit size can be combined in various ways that satisfy total growing area function. However, solutions only present a short range of DAT, typically between 19.9 to 20.5 days, regardless of the constraint. This indicates that the objectives may not be conflicting except within this specific range. This can be further understood by optimizing EBT and EUE as single objectives. EBT is solely a function of DAT, as illustrated in Figure 3. EBT is optimized at a single point, and the solution DAT is 19.9.

The reason for this is that when DAT is relatively short, the daily harvest increases faster than total energy usage as DAT increases. However, this trend reverses when DAT is relatively long. In shorter DAT, the EUE improves because the head mass per plant is greater, resulting in an increased total daily harvest. On the other hand, with a longer DAT, the lettuce requires more electric energy to grow in later stage, leading to a longer period of higher electricity use for lettuce growth. As a result, EUE improves in DAT until it reaches the optimum level of 19.9 and then begins to decline beyond this point.

On the other hand, EBT is a function of DAT, base unit size, and distance to the urban center. The objective is observing how EBT changes as DAT varies while keeping the total growing area fixed. Figure 3.4 illustrates EBT as a function of DAT and base unit size, assuming a distance to the urban center of 3 km and a total size of growing area of 100m^2, which corresponds to the case in the first column of Table 4. Since the total size of the growing area is fixed at 100m^2, there is a unique DAT satisfies the size constraint for a given base unit size, and vice versa. Therefore, Figure 3.4 shows the trajectory of EBT for those combinations of DAT that satisfy the size constraint. EBT is maximized at a single point, and the solution DAT is 20.5.

Furthermore, the solution DAT remains the same regardless of the size constraint. Intuitively, EBT increases with DAT because increasing DAT leads to higher yield. Since lettuce grows faster in later stage, there is an upward pressure for DAT to make the most of the relatively faster growth period of the lettuce and maximize yield. However, longer DAT inevitably increases costs due to higher energy use. Energy use is more intensive in the production stage, given higher PPFD utilized, relative to the propagation stage. Hence the optimum level of DAT that maximizes the single objective EBT is determined under these trade-offs.

For that reason, solution DAT is ranging from 19.9 to 20.5 regardless of the size constraint (Table 3.4). Results confirmed that EBT and EUE are not conflicting objectives, except for this range. Both EBT and EUE improve as DAT increases when DAT is shorter than 19.9 and decline as DAT increases when DAT is longer than 20.5. This intuitively makes sense because efficient energy utilization can contribute to the profitability of IA, as it helps mitigate the operational costs associated with energy consumption. However, the two objectives are not necessarily always aligned. This study found a limited DAT range, from 19.9 to 20.5 days, where two objectives are conflicting when the farm size remains fixed. At the optimal level, fine-tuning the production schedule becomes crucial in order to achieve an optimal balance between the two objectives, considering specific preferences and priorities.

In a 'what if' scenario analysis, this paper explored the cases where the total growing area cannot exceed certain levels. Since it is not always possible to mobilize capital to achieve a significant level of economies of scale, it is important to consider varying size constraints and investigate the optimal operation strategy for various size of IA farms. In Table 3.4, the optimal distance to the urban center increases as the size constraint is relaxed. It is important to note that the optimal distance in these model simulations were set at 3 km, 30 km, or 60 km.

Since the land price is assumed to be the same within the same region of urban, suburban, or rural areas, model solutions will favor proximity to urban center to save on transportation cost and gain revenue through hyper-local premium within each region. Hence, the solution distance will be at 3 km, 30 km, or 60 km to the urban center. Figure 3.5 shows the potential farm locations in the New York City metropolitan area. Point A, B, and C represent the possible solutions for the locations in urban, suburban, and rural areas with distances to the urban center of 3 km, 30 km, and 60 km, respectively.

Interestingly, urban areas are the optimal location for 100 m^2 and 800 m^2 farms, but suburban and rural area are optimal for 2,000 m^2 and 100,000 m^2 farms, respectively. This means that for relatively small size farms, it is better to take advantage of a hyper-local premium and save transportation cost despite the expensive land price. However, if one can raise capital to achieve significant level of economies of scale, moving away from urban center to save land cost is best strategy to maximize profit. This implies that different locational strategies can be employed for IA systems of varying sizes.

Since relatively small farms can perform better in urban areas than in suburban or rural areas, small-sized IA systems can be an economically sustainable format to serve specific purposes from diverse spots in urban areas, such as hospitals, schools, shopping centers, etc. (Takagaki et al., 2020). This approach serves not only as an eye-catching feature but also as a practical way to cater to hyper-local consumers. At the same time, large-scale IA operations can play a major role in providing the urban population with a steady supply of fresh produce, even if they are located slightly outside the urban center.

3.4 Conclusion

In this paper, an optimization tool for IA production systems (IA-MOO) in metropolis is presented to achieve both profitability and energy use efficiency, which are necessary conditions for IA systems to be a sustainable agricultural production method. To create a comprehensive tool, IA-MOO integrates three modules: a production module with detailed production optimization model, a cost module with economies of scale, and a revenue module with IA-produced and hyper-local price premium model. By using production schedule, farm size, and farm location as decision variables, this study draws implications for the optimal production planning and farm design strategies in the IA industry.

I found that economies of scale play a significant role in this industry. All non-dominant solutions are clustered around the upper bound of size constraints, indicating that maximizing economies of scale can effectively increase profitability. This is true even when farm size is relatively small due to constraints. Additionally, it was observed that EBT and EUE are generally not conflicting objectives, except for a short production schedule window where the two objectives contradict each other. This means that it is possible to optimize both objectives without significantly compromising one of the objectives.

Furthermore, this paper discovered that the optimal location for a relatively small-sized IA farm is within an urban area, while for a relatively larger-sized IA farm, it is outside of an urban area. This suggests that strategic planning should be tailored to the farm's size and location to effectively serve urban consumers. For instance, small-sized farms may find success by integrating into large building structures where a consistent supply of fresh produce is required, such as schools, hospitals, or shopping malls. In contrast, larger-sized IA farm can focus on meeting the entire demand in the metropolitan area from their optimal locations.

The IA-MOO model framework offers a high level of flexibility, enabling it to be applied in diverse circumstances by incorporating different parameterizations that consider variations in economic, geographic, and resource conditions. Nevertheless, it is essential to understand that the IA-MOO model does not aim to determine the best business model or the ideal design for an IA farm. Given the inherent complexities and real-world variations, actual IA systems may exhibit significant differences in their specific details. The primary goal of this paper is not to advocate for a particular type of IA operation or assume a standardized IA farm model. Instead, it used a hypothetical design to provide valuable insights into optimizing IA systems to achieve both profitability and energy use efficiency.

Future studies in the IA industry can explore additional objectives that IA systems may aim to achieve. If optimally designed and strategically located, IA has the potential to enhance social welfare (Kozai & Niu, 2020), such as by addressing the problem of 'food deserts'. Food deserts are significant issues in urban areas of the United States, and ongoing research is investigating the extent to which IA can contribute to eliminating these food deserts (Luongo, 2023). The IA-MOO framework can be leveraged to investigate the optimal size and location of IA farms to effectively reduce food deserts while considering both economic and environmental sustainability aspects simultaneously. Furthermore, it will be useful to incorporate traditional greenhouse and farm operations, as well as additional lettuce varieties, into the model options to compare IA systems with these alternative growing technologies and crops. Since conventional agricultural practices and IA farms can serve different roles based on their comparative advantage, it is more likely that adopting different farm options in various locations can yield better outcomes rather than adopting a one-size-fits-all approach. The present study investigated the production of a specific blend of lettuce variety, but other lettuce varieties or crops can be explored to identify the optimal crop choice, provided that plant growth data is available.

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APPENDIX: TABLES AND FIGURES

Table 3.1 Model input data on revenue model parameters

Parameter	Variable	Value	Unit	Source
Lettuce price				
IA grown lettuce	P_{IA}	4.808	\$/4.5oz	Seong et al. (2023)
Hyper-local premium	P_{hl}	10	%	Set by author
Retailer margin	*RetM*	50	%	Set by author
Radii of areas defining zones				
Suburban	r_2	60	km	Set by author
Urban	r_1	30	km	Set by author
Hyper-local	r	15	km	Set by author

Table 3.2 Model input data on cost module parameters.

Parameter	Variable	Value	Unit	Source
Variable costs				
Energy				
Electricity cost	P_e	0.10	$/kWh	Shasteen et al. (2022)
HVAC load	HV	30	%	Shasteen et al. (2022)
Labor				
Wage	w_h	12.46	$/hour	
Benefit load	w_b	20	%	Shasteen et al. (2022)
Seedling and planting	L_s	1.8	%	Shasteen et al. (2022)
Transplanting	L_t	5.5	%	Shasteen et al. (2022)
Harvest	L_h	23.6	%	Shasteen et al. (2022)
Packaging	L_p	23.6	%	Shasteen et al. (2022)
Cleaning	L_c	45.5	%	Shasteen et al. (2022)
Consumable				
Seed price	P_s	$a_{seeds} = 0.424$, $b_{seeds} = -0.253$	$/seed	Set by author
Substrate cost	P_m	0.035	$/unit	Shasteen et al. (2022)
Packaging cost	P_p	0.04	$/4.5oz	Shasteen et al. (2022)
Transportation				
Diesel cost	P_d	0.36	$/km	Set by author
Average motor carrier cost	P_{amcc}	1.58	$/km	National Private Truck Council (2021)
Fixed costs				
Building and technology		$a_{capital} = 7122.399$, $b_{capital} = 0.829$	$	Zhuang et al. (2022)
Life span	LS	15	year	Zhuang et al. (2022)
Annual maintenance	δ	1.5	%	Zhuang et al. (2022)
Mortgage amortization				
Annual interest rate		6.2	%	Nicholson et al. (2020)
Term		10	year	Nicholson et al. (2020)
Land price				
Urban	P_L	586.88	$/m^2$	Nicholson et al. (2020)
Suburban	P_L	293.44	$/m^2$	Set by author
Rural	P_L	146.72	$/m^2$	Set by author

Table 3.3 Model input data on production module parameters.

Parameter	Variable	Value	Unit	Source
Plant growth				
Transplanting		1	Per cycle	Shasteen et al. (2022)
Harvest		360	Per year	
Propagation stage length	*DBT*	14	Days/cycle	Shasteen et al. (2022)
Propagation stage density	*DenBT*	1550	Plants/m^2	Shasteen et al. (2022)
Lighting				
Photo period	*PhPer*	16	Hours/day	Shasteen et al. (2022)
Lighting efficacy	ηPAR	2.5	µmol /J	Shasteen et al. (2022)
PPFD in propagation stage	$PPFD_{propagation}$	140	µmol/m^2·s	Shasteen et al. (2022)
PPFD in production stage	$PPFD_{production}$	200	µmol/m^2·s	Shasteen et al. (2022)
DLI in propagation stage	$DLI_{propagation}$	8.06	mol/m^2·day	Shasteen et al. (2022)
DLI in production stage	$DLI_{production}$	11.52	mol/m^2·day	Shasteen et al. (2022)
Space use				
Number of tiers in propagation stage	*ShelfProp*	8		Shasteen et al. (2022)
Number of tiers in production stage	*ShelfProd*	4		Shasteen et al. (2022)
Corridor space	*Corrid*	37.5	%	Uraisami (2022)
Growing structure space	*Facility*	30	%	Eaves & Eaves (2018)
Additional space	*Additional*	55.8	%	Eaves & Eaves (2018)

Table 3.4 Solutions and associated scenario by constraints on total growing area.

Variables	Constraints on total growing area (m^2) <100	 <800	 <2000	 <100,000	Unit
Objectives					
EUE	11.20 – 11.23	11.20 – 11.23	11.20 – 11.23	11.20 – 11.22	kWh/kg
EBT	5.0 – 5.3	230.5 – 232.4	730.6 – 735.3	58,881.2 – 59,084.4	$’000/year
Solutions					
DAT	19.9 – 20.5	19.9 – 20.5	19.9 – 20.5	19.9 – 20.5	days
Base unit size	0.12 – 0.11	0.93 – 0.86	2.33 – 2.14	116.28 – 107.45	m^2
Distance to urban center	3	3	30	60	km
Production and revenue					
Total growing area	100	800	2000	100,000	m^2
Total land area	69	552	1382	69,099	m^2
Daily harvest	14.8 – 14.8	118.2 – 118.1	295.6 – 295.1	14,780.5 – 14,758.0	kg/day
Daily energy use	165.6 – 165.7	1324.7 – 1325.2	3311.0 – 3313.0	165,586 – 165,649	kWh/day
Wholesale price	2.46	2.46	2.43	2.40	$/4.5oz
Annual revenue	102.8 – 102.6	822.2 – 820.9	2027.3 – 2024.5	100,269 – 100,116	$’000/year
Fixed costs					
Building and technology	324	1817	3883	99,454	$’000
Land	41	324	406	10138	$’000
Mortgage payment	4.1	24.0	48.0	1227.7	$’000/month
Depreciation and maintenance	26.5	148.4	317.1	8122.2	$’000/year
Variable costs					
Transportation	2.5	2.5	24.9	99.6	$’000/year
Consumables	5.6 – 5.3	39.4 – 37.5	94.2 – 89.8	4224.1 – 4032.7	$’000/year
Labor	8.2 – 8.1	66.0 – 64.6	164.9 – 161.5	8249.3 – 8081.3	$’000/year
Energy	6.0 – 6.0	47.7 – 47.7	119.1 – 119.3	5961.1 – 5963.4	$’000/year

Table 3.5 Productivity and financial performance of solutions by size.

Variables	Total growing area (m^2) 100	800	2000	100,000	Unit
Production productivity					
Fresh weight	0.148	0.148	0.148	0.148	$kg/m^2 \cdot day$
Cost productivity					
Unit investment cost of building and technology[a]	3.2	2.3	1.9	1.0	$'000/$m^2$
Financial index					
EBT per m^2	50.0 – 52.8	288.1 – 290.5	365.4 – 367.7	588.8 – 590.8	$/$m^2 \cdot year$
EBT margin[b]	4.9 - 5.1	28.0 - 28.3	36.0 - 36.3	58.7 - 59.0	%

[a] Cost of investment in building and technology for 1m^2 of growing area. It is decreasing in the size of total growing area due to economies of scale.
[b] EBT margin represents the percentage of profits an IA farm retains prior to paying taxes.

Figure 3.1 IA-MOO framework.

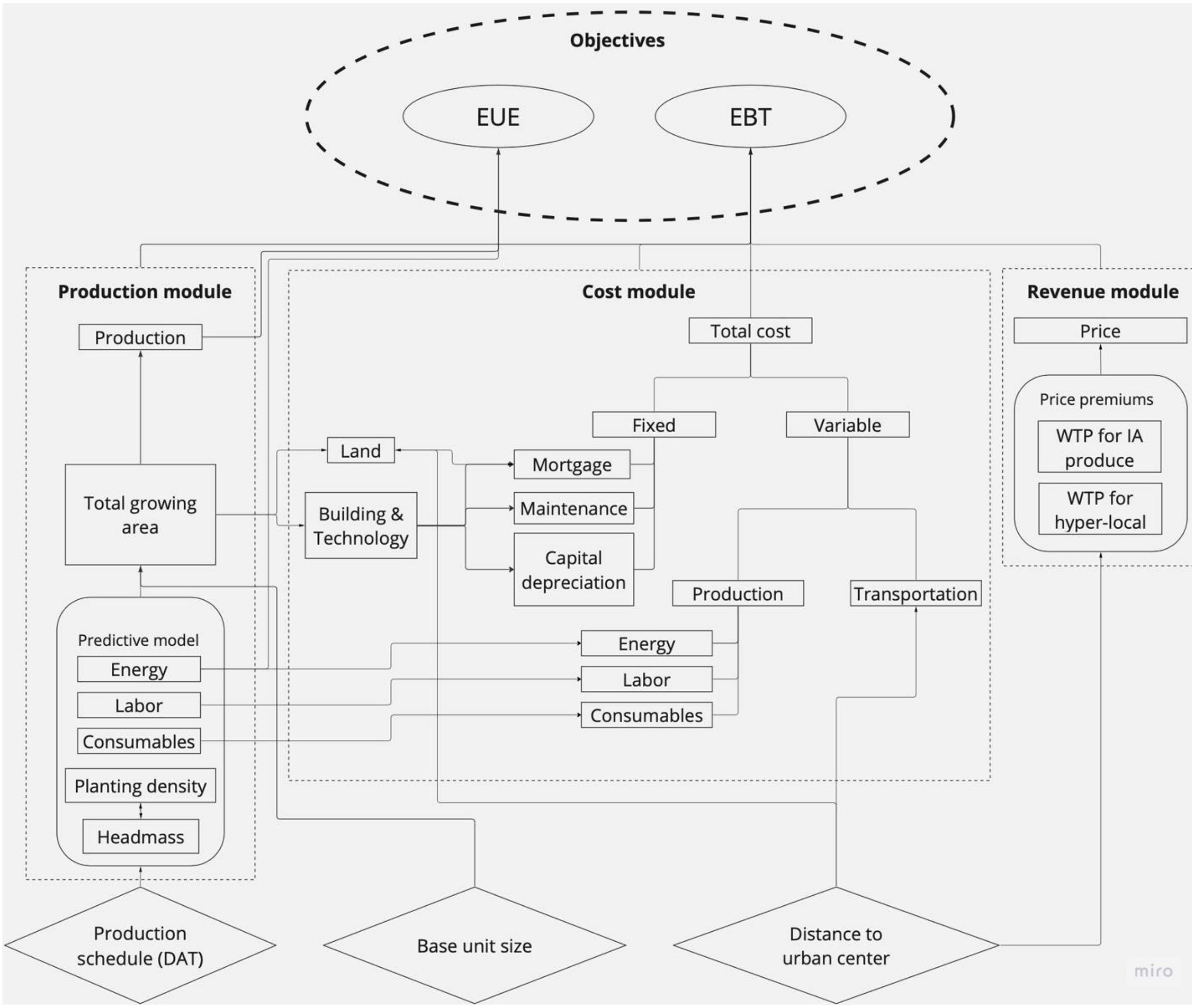

Figure 3.2 Pareto fronts with constraints on total growing area.

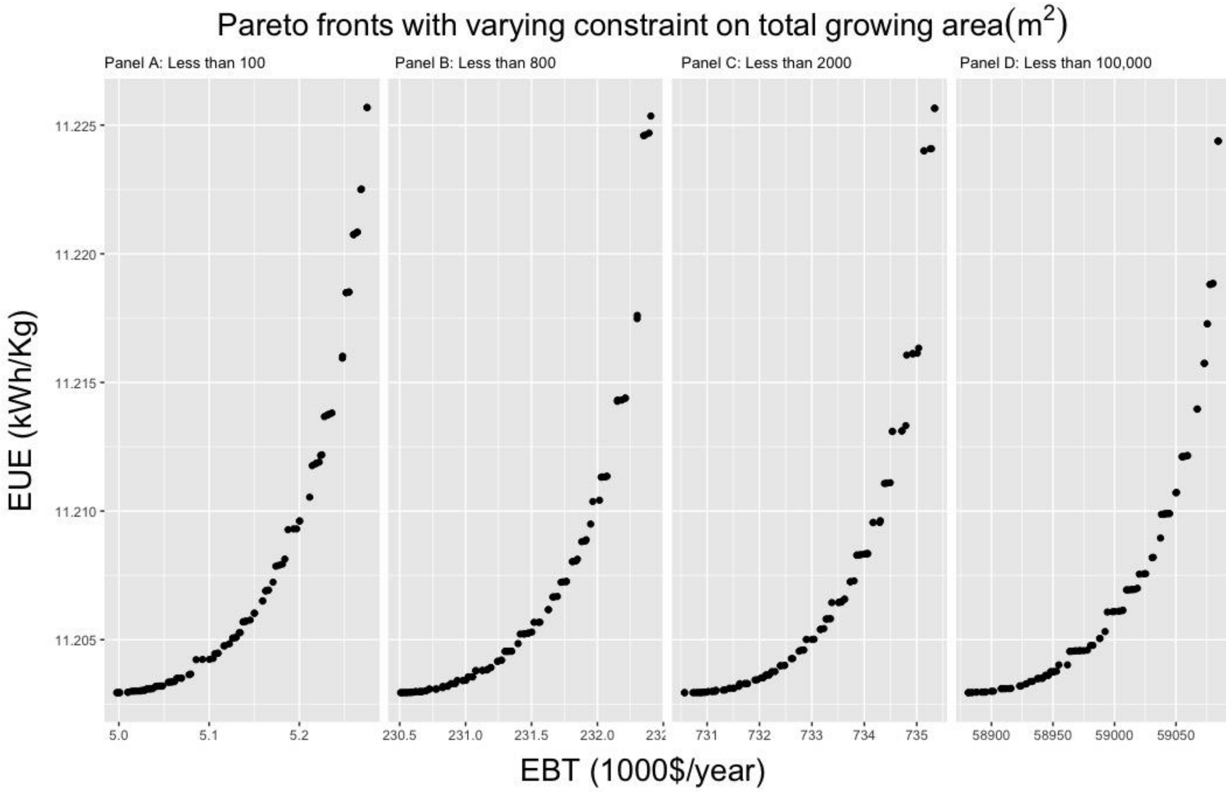

Figure 3.3 Single objective optimization – EUE.

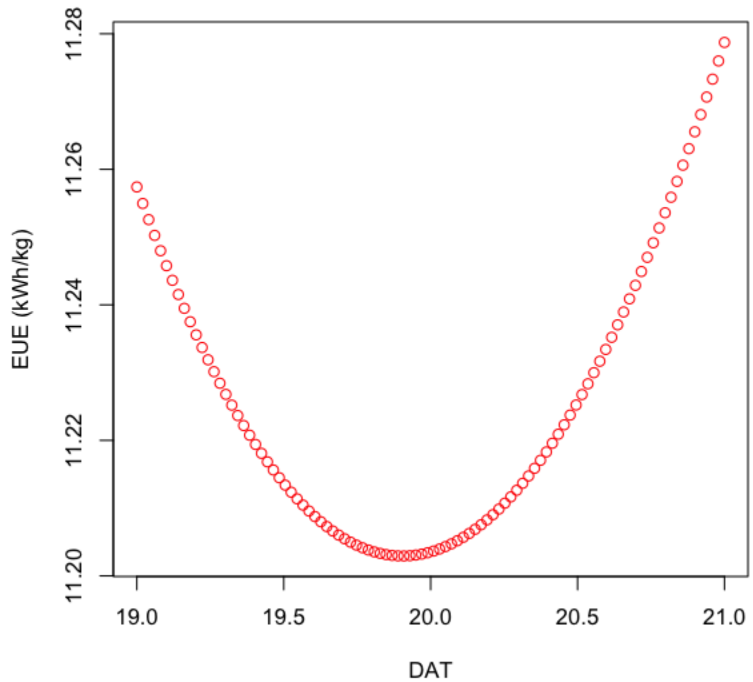

Figure 3.4 Single objective optimization – EBT size constraint.

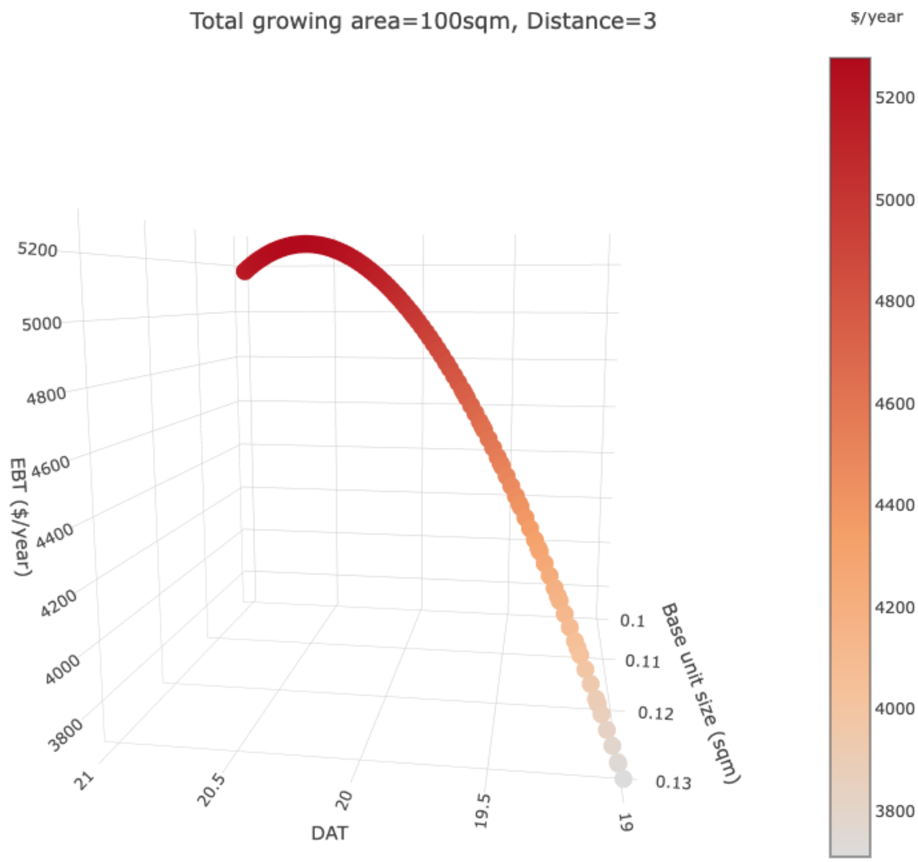

Figure 3.5 New York City metropolitan area and potential farm locations.