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Analysis of Food Hub Commerce and Participation using Agent-Based Modeling: Integrating Financial and Social Drivers

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Abstract

Objective: Factors influencing long term viability of an intermediated regional food supply network (food hub) were modeled using agent-based modeling techniques informed by interview data gathered from food hub participants. **Background**: Previous analyses of food hub dynamics focused primarily on financial drivers rather than social factors, and have not used mathematical models. **Methods**: Based on qualitative and quantitative data gathered from 22 customers and 11 vendors at a Midwestern food hub, an agent-based model (ABM) was created with distinct consumer personas characterizing the range of consumer priorities. A comparison study determined if the ABM behaved differently than a model based on traditional economic assumptions. Further simulation studies assessed the effect of changes in parameters such as producer reliability and the consumer profiles on long-term food hub sustainability. **Results**: The persona-based ABM model produced different and more resilient results than the more traditional way of modeling consumers. Reduced producer reliability significantly reduced trade; in some instances a modest reduction in reliability threatened the sustainability of the system. Finally, a modest increase in price-driven consumers at the outset of the simulation quickly resulted in those consumers becoming a majority of the overall customer base. **Conclusion**: Results suggest that social factors such as desire to support the community can be more important than financial factors. **Application**: An agent-based model of food hub dynamics, based on human factors data gathered from the field, can be a useful tool for policy decisions. Similar approaches can be used for modeling customer dynamics with other sustainable organizations.

Keywords: Sustainability, dynamic systems modeling, ethnographic observations, organizational behavior

Précis: A predictive model of food hub sustainability was created using human factor knowledge elicitation techniques with a United States Midwestern food hub and agent-based modeling. Results suggest that social factors such as desire to support the community are more important than financial factors.

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Introduction

What motivates people to participate in sustainable projects, especially when a simple financial analysis does not add up? We know from cognitive science research that human beings do not use "rational" or traditionally logical reasoning processes (Johnson-Laird, 1983; Tversky & Kahneman, 1974), and that psychological barriers can prevent ongoing participation in sustainability initiatives (McKenzie-Mohr, 2000). This current research addresses one instance of this broad question, and in doing so, seeks to offer an analytical human factors-based approach that can apply to other contexts as well. This effort focuses on what motivates food producers and consumers to participate in a particular United States Midwestern food hub. The question is answered using data gathered from participants and an agent-based model based on those data. While previous analyses of food hubs have been primarily financial, the current approach, using the human factors principles of creating a quantitative model grounded in participants' motivations gathered from the field, yields a richer analysis with new insights.

A food hub is an organization that facilitates the distribution of primarily locally grown source-identified food from farmers to customers (Barham et al., 2012). “Source-identified” means that information about the vendor of the food remains with the food as it is supplied. The definition of “food hub” is not strict; a membership-based food co-op could qualify as a food hub, as could a community-supported agriculture (CSA) initiative that brings boxes of food to a central site for distribution. The key feature of a food hub, however, is typically that it offers more supply chain management than, say, a farmers market, to offer higher volume to customers such as restaurants or local-focused grocery stores, as well as to consumers (see Figure 1). An average food hub, according to a 2013 benchmarking report (NGFN Food Hub Collaboration, 2013), has 79 vendors and 326 customers (22% restaurants and 43% grocery). A 2012 report by the USDA (Barham et al., 2012) identified 168 regional food hubs in the US.

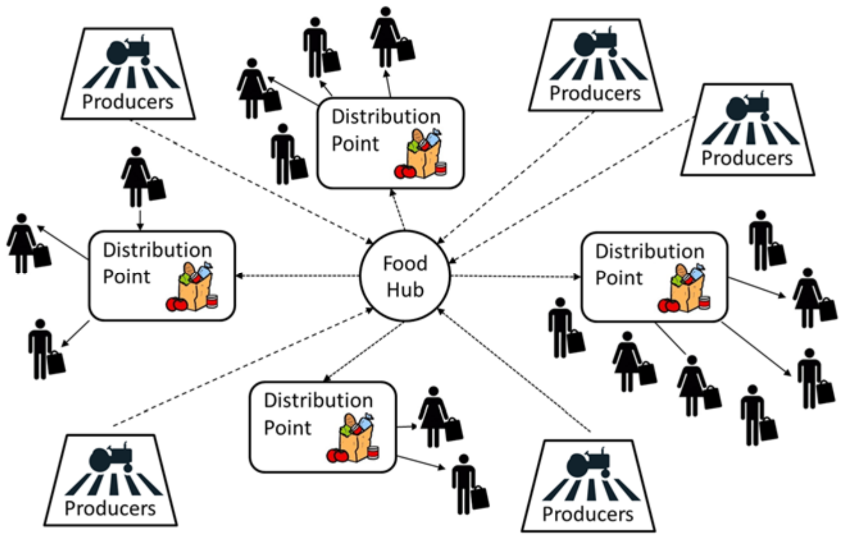

Figure 1. Structure of the Food Hub studied.

While food hubs have demonstrated numerous community benefits, such as increasing access to healthy food and supporting rural workforce development, the Barham USDA report (2012) notes that they face endemic challenges in balancing supply and demand, resistance to paying a premium price for local fresher products, and managing growth if they are successful. Note that these challenges described by the USDA are financial. While they are certainly valid, especially when considering a food hub to be a business venture, the authors suggest that human constructs such as trust and the motivation to be green or to support the local economy are forces that merit equal consideration in predicting the success of a food hub venture.

Research Questions and Overall Approach

This research addresses three research questions. First, what are the motivational factors influencing food hub members' participation? Second, if we develop a simulation model grounded in these data, does it behave differently than a model based on traditional economic assumptions? Lastly, what insights can this model reveal about the dynamics of food hub participation? These questions are addressed in a sequence of four studies. Study 1 describes the food hub data elicitation from participants. In Study 2, an agent-based simulation is developed based on Study 1 data and compared with a model using traditional assumptions without such data. In Studies 3 and 4, the simulation model is used to explore the success of a food hub under varying conditions.

Related Research

This section provides the motivation for studying sustainability in food systems. Further, the relevance of regional food hubs in supporting long-term social and environmental sustainability in food systems is established. Finally, we describe agent-based modeling and explain why it is an appropriate methodology for the study of the decision making, behaviors, and interactions among regional food hub producers and consumers.

Food Hubs

The modern industrial food system feeds six billion people (Tilman, Cassman, Matson, Naylor, & Polasky, 2002). However, there are many negative external threats associated with industrial food supply chains, including toxins released into the environment (e.g., greenhouse gases and pollution due to pesticide and nutrient run-off) and an unsustainable rate of energy and water consumption (Godfray et al., 2010). These problems, which stress the very inputs to the system that enable its productivity, are compounded by problems of resource overconsumption, climate-change-induced precipitation and temperature variability, and changes in the frequency and severity of extreme climate events (Nelson et al., 2009; Parry et al., 2007). Maintaining the food system’s long-term productivity without compromising long-term future environmental and public health is a major challenge.

By contrast, localized food systems, which reduce the number of intermediaries and geographic distance between producers and consumers, can reduce the energy and ecological costs of long-distance transportation while redistributing value along the supply chain (Bloom & Hinrichs, 2010). Such systems may also enable consumers to demand greater producer accountability for ecological degradation (Iles, 2005). While the industrial food system supports regional specialization and large-scale monoculture production, localized food systems have a decentralized structure and regionally-diverse output, which increases their resilience and stability in the face of change (e.g., climate change impacts, fluctuating energy costs) (Clancy & Ruhf, 2010; Dalhberg, 2008). Proponents of localized food systems believe that they offer a safer, healthier, and more sustainable alternative to the industrial food system, and consumers are increasingly choosing food that is produced locally and sustainably. Their reasons vary widely, from saving money, to wanting to ensure food nutrition, quality, freshness, and safety, to concerns over environmental implications and the treatment of farm workers, to a desire to support the local economy and have a connection with the person who produced their food (Brown, 2002; Brown, 2003; Wolf, Spittler, & Ahern, 2005). The local food movement has grown tremendously in the past decade, with direct-to-consumer food sales in the U.S. increasing three-fold from 1992 to 2007 (from $404 million to $1.2 billion), and the number of farmers' markets listed in USDA National Farmers Market Directory has increasing more than four-fold from 1994 to 2013 (Tropp, 2013). According to the National Grocery Association, 87.2% of consumers regard the availability of locally-produced food as important in their grocery shopping decisions (Tropp, 2013). Federal, state, and local policymakers are incorporating local foods into programs designed to reduce food insecurity, support small farmers and rural economies, encourage more healthful eating habits, and foster closer connections between farmers and consumers (King et al., 2010).

This increase in demand has been extraordinarily beneficial to small- and medium-scale food producers. Traditionally, the most common market channels for these producers have been direct-to-consumer, via farmers' markets and community supported agriculture (CSA) programs. Producers typically get better prices at the farmers' market than through wholesale outlets (Myers, 2011), and farmers' markets are ideal venues for producers who have limited quantities of a large variety of products. However, these direct-to-consumer outlets are highly labor-intensive and are not very profitable for producers on average, due to low sales volumes, competition from multiple sellers, and high transportation and marketing costs (LeRoux, Schmit, Roth, & Streeter, 2010; Tropp, 2013). To avoid the challenges associated with direct-to-consumer sales, many small- and medium-scale producers would prefer to sell to larger-scale customers (e.g., grocery stores, restaurants, schools), either directly or through a distributor.

However, the structure of conventional industrial food systems is not conducive to localized distribution. In particular, the participants highly value economies of scale. Institutional buyers tend to aggregate their purchases for logistical convenience, and distributors provide them with incentives for meeting specified purchasing volumes (Feenstra, Allen, Hardesty, Ohmart, & Perez, 2011). Medium- and small-sized producers struggle to participate within this system because they lack the necessary scale to satisfy large-scale distributor volume, quality, consistency, variety, availability, and price point requirements (Kirby, Jackson, & Perrett, 2007). They are also challenged by a lack of distribution, processing, and marketing infrastructures that would give them wider access to larger-volume customers, as well as high logistics and transportation costs (Bosona, Gebresenbet, Nordmark, & Ljungberg, 2011; Diamond & Barham, 2012; Tropp, 2013).

One potential solution to this problem is the development of regional food hubs. A regional food hub provides small- and medium-scale food producers an alternative to direct-to-consumer sales, in which the aggregated output of many smaller farmers is large and consistent enough to fulfill the needs of larger institutional customers. This often changes the role of the small-to-medium-sized farmer from "price-taker" to "price-maker." A food hub can improve economic sustainability in a region by creating new farming opportunities, providing existing small- and medium-sized farmers with better incomes, and by creating new warehousing, food processing, packing jobs at the hub (Barham, 2011). In addition to helping farmers economically, food hubs can also support regional social and environmental sustainability. For example, more than 40 percent of existing food hubs in the U.S. are specifically working in "food deserts" to increase access to fresh, healthful and local products in communities underserved by full-service food retail outlets (Merrigan, 2011).

Sufficient producer participation is critical to a regional food hub's long-term success and economic sustainability. Successful hubs are typically those that are able to gross sales of $2 million or more (sourcing from at least 40–60 suppliers), carry a variety of different products, and provide year-round operations (Barham, Carmody, Collier, Cullen, & Fisk, 2011).

Agent-Based Modeling

Mathematical optimization has been the most commonly used methodology for modeling food systems. Most existing agricultural optimization models are static and deterministic linear programming models with a single objective of maximizing short-term farm income or profit, subject to constraints of farm input costs or availability constraints (Ahumada & Villalobos, 2009; Janssen & van Ittersum, 2007). Some models address environmental sustainability issues as well, typically through multi-objective optimization of resource consumption and/or crop rotations. Such models tend to capture the operations of a single farm and then aggregate these effects to represent the regional behavior, which does not account for heterogeneous actor behaviors, nor does it account for the dynamic interactions and adaptations that occur among food system actors over time. Very few of these models are able to capture stochastic or dynamic elements of food systems, nor are they capable of modeling the sociological processes that influence decision-making by farmers (Higgins et al., 2010).

By contrast, agent-based modeling (ABM) is a modeling tool that is well-suited to capturing the complexity of dynamic and stochastic regional food systems, particularly the behaviors, decisions and interactions of the autonomous, intelligent, and interconnected actors that inhabit them (Choi, Dooley, & Rungtusanatham, 2001; Meter, 2006). Unlike traditional optimization models, ABM can accommodate heterogeneous actor objectives, behaviors, dynamic interactions, and adaptations that occur among humans over time. ABM models multiple autonomous agents (actors) that have intelligence (internal logic), as well as the ability to make complex decisions and engage in complex interactions with other agents and objects within their environment. Such interactions lead to dynamic agent adaptations; that is, the ability to apply new knowledge to future decisions and behaviors. Some agents may be more influential than others, but none completely controls the behavior of the system (North & Macal, 2007). The dynamic interactions among individual agents and the objects in their environment result in a system that exhibits behavior that cannot be predicted by examining the behavior of its individual parts (Pathak, Day, Nair, Sawaya, & Kristal, 2007). Such system behavior and resultant properties are said to be emergent (Gilbert & Troitzsch, 2005). ABM is therefore a particularly appropriate tool for capturing the complexity and emergent behavior of regional food systems, including the behaviors, decisions, and interactions of the autonomous, intelligent, and interconnected human actors (i.e., food producers and consumers) that inhabit them.

Existing ABMs of food systems are almost exclusively focused on a single echelon: crop production (see Krejci & Beamon, 2012 for a review). These models typically capture the impacts of farmers' decisions on regional land use and shared resource consumption (e.g., Balmann, 1997; Becu, Perez, Walker, Barreteau, & Page, 2003). Some models also capture the impact of farmers' decisions on the environment by embedding crop simulation software and/or functions within the model (e.g., Belem, et al., 2006; Happe, Hutchings, Dalgaard, & Kellerman, 2011; Janssen, 2001). Krejci and Beamon (2015) developed an ABM to study the impact of farmer coordination on the development of regional food system structures and social sustainability outcomes. However, this model did not incorporate the food consumers as agents, and it was based on a stylized theoretical regional food system, in which producer behavior was modeled after assumptions from the scholarly literature and informal conversations with regional food system participants. There is a need for ABM for regional food systems with empirically-derived inputs, which will allow for a more realistic representation of a food system and its constituent actors.

Study 1: Knowledge Elicitation

In this study we designed both a consumer- and producer-based structured interview to establish empirically based practices of both groups. Prior work has relied on assumptions made by domain experts and food hub personal. The output of this work was later used to develop accurate personas that were then used in multi agent simulations.

Methodology

Research Objectives. The objective of the knowledge elicitation (Cooke, 1994) sturctured interviews was to develop an accurate understanding of both consumer and producer as they relate to food hub operations by making their implicit expertise explicit. Determining characteristics that relate to buying practices, participation motivations, and values would be used to develop personas within the ranks of the food hub consumers that would later be used to inform an agent-based model.

Participants. Interviews were conducted with a total of 33 individuals in the Des Moines, Iowa, area. Participants were recruited per methods approved by the Institutional Review Board using email of consumers and producers affiliated with a regional food hub. Participants were 18 years of age or older.

The 22 consumers (19 female, 3 male) averaged 48.5 years of age (range 28-78) with a median income of $100,000 (range $40,000-$300,000). On average they live 6.5 miles (SD=3.2) from the food hub. The average number of the people in the household was 2.5 (SD=1) and 18 participants were the primary shopper for the household. They had a high comfort level with technology (M=4.5, SD=0.7 on a 5-point scale), and 19 had a college degree.

The 11 producers (5 female, 6 male) averaged 49.1 years of age (range 28-67) with a median income of $78,000 (range $13,000-$175,000). On average they lived 39.8 miles (SD=22.7) from the food hub. The average number of the people in the household was 3.4 (SD=1). They had a high comfort level with technology (M=3.9, SD=1.0), and 6 had a college degree.

Interview Survey. Separate but parallel versions of the surveys were created for consumers (42 questions, Table 1) and producers (31 questions, Table 2). The questions were designed to both elicit qualitative information (via open-ended questions) and quantitative information (Likert rating scale of 1 to 5).

Table 1. Interview survey for consumers.

Category	Number	Description
Activity Level at Food Hub & Shopping Profile	17	Spending profile, changes in activity level; order profile; types of food purchased, availability, selection, fraction of overall food bought at hub, repeat vendor sales, issues with vendors, satisfaction rating, changes in shopping behavior
Communication	14	Communication with other members, recruitment of non-members, Frequency of contact with food hub vendors, purpose of contact with food hub vendors, familiarity with vendors, depth of relationship with vendors, methods used to contact vendors, satisfaction with vendor contact, how problems/issues have been resolved with vendors, responsiveness of vendors and food hub staff
Online Exposure	9	Positive and negative attributes of the website, usability of the website, frequency of access, usefulness of provided information, information that consumers wish to see with regards to vendors and vendor operations, overall usefulness of the website, aspects of vendor profiles that encourage or discourage purchasing behavior
Values	2	Rate importance of price, convenience of food preparation, nutrition, freshness, familiarity, novelty, convenience, variety, supporting of local economy, relationship with producers, communicate with vendors, food production practices, food safety, treatment of animals

Table 2. Interview survey for producers.

Category	Number	Description
Activity Level at Food Hub	14	Selling profile, changes in activity level; vendor profile; types of food offered for sale, amount of stock sold to food hub and alternative outlets, factors influencing sales, frequency of offerings, revenue earned from sales, number of customers sold to, number of repeat customers, average size of customer order, historic level of sales activity, satisfaction rating
Communication	11	Communication with other producers, Frequency of contact with food hub consumers, purpose of contact with food hub consumers, familiarity with consumers, depth of relationship with consumers, methods used to contact consumers, satisfaction with vendor contact, how problems/issues have been resolved with consumers, relationship with consumers and food hub staff
Online Exposure	5	Positive and negative attributes of the website, usability of the website, frequency of access, usefulness of provided information, perception information that consumers wish to see with regards to operations, overall usefulness of the website, aspects of vendor profiles that encourage or discourage purchasing consumers behavior
Values	2	Rate importance of price, convenience of food preparation, nutrition, freshness, familiarity, novelty, convenience, variety, supporting of local economy, relationship with producers, communicate with vendors, food production practices, food safety, treatment of animals

Data Analysis. Open ended responses were transcribed into a spreadsheet and then categorized. For example, consumer purchases were categorized into seven categories: vegetables, fruits, meats, dairy, eggs, processed foods, and none-food items. Counts of responses in each category were used to develop distribution profiles. Economic activity data from the food hub were also analyzed.

Hierarchical cluster analysis (Everitt, Landau, Leese, & Stahl, 2011) was used to categorize consumers based on answers to the 14 "values" questions (ratings on a Likert scale 1-5). Since the values questions were somewhat broad, responses were standardized using z-scores to minimize the possible effect of participants conceptualizing different questions differently. Because standardization can sometimes decrease the distance between clusters, squared Euclidean distance was used as the metric to emphasize greater distances. Multiple clustering methods (nearest neighbor, furthest neighbor, and Ward's method) were examined to ensure that the resulting clusters were consistent. The number of clusters was chosen using the coefficients of the agglomeration schedule, looking for the first noticeable increase.

Limitations and Assumptions. While the interviews were extensive, the sample of consumers and producers was self-selected. The personas developed were based on the feedback from this group. This method for interviewee selection and persona development has been widely used (Adler, 2005; Aquino & Filgueiras, 2005).

Study 1 Results

Activity Level at Food Hub & Shopping Profile. Activity levels of both consumers and producers are summarized in Table 3. Both groups were very similar in duration of affiliation, and have a very high overall satisfaction with the food hub. Nearly three quarters of the consumers purchase from the food hub every cycle with the remaining purchasing every other cycle. Producers, however, overwhelmingly participated every cycle. Almost three quarters of consumers maintained the same activity level since they joined the food hub, 27% increased their activity, and 9% decreased their purchasing activity.

Table 3. Activity level of Consumers and Producers. Numerical results are: means (standard deviations).

Attribute	Consumer	Producers
Time affiliated with Food Hub	3.0 years (2.3)	3.2 years (2.1)
Cycles of participation	16 every cycle, 6 every other cycle	8 every cycle, 1 a few times a year
Activity level since joining	14 no change, 6 increased, 2 decreased	4 no change, 5 increased, 2 decreased
Amount of money spent / earned per cycle	83.7 USD (47.7)	257.0 USD (170.5)
Do you purchase / sell from same vendor / consumer	17 Yes, 5 No	8 Yes, 1 No
If experience a problem with a vendor how likely are you to buy from them again?	3.4 (1.5)	4.1 (0.6)
Rating of overall food hub experience (1 not likely – 5 very likely)	4.7 (0.5)	4.4 (0.5)

Food hub consumers and producers were likely to shop/supply multiple food supplying establishments. Food hub consumers largely reported that they would be willing to increase their purchase activity if the food hub was more retail-like and/or easier to get to. Producers reported that they would increase supply primarily if the food hub had lower fees (several producers expressed issue with having to mark items up compared to other sales channels). Both consumers and producers reported having a high likelihood to buy from or sell to one another, and a fairly positive attitude toward product issues and resolutions.

Communication. Both groups were very similar terms of their moderate estimate of the relationship between vendor and customer and positive impression of past communication experiences (see Table 4). The majority of both groups had contact every cycle or every other cycle with communication often having to do with product questions, product issues or special requests.

Table 4. Communication activities between Consumers and Producers.

Attribute	Consumer	Producers
Do you share information with vendors / consumers?	13 Yes, 9 No	6 Yes, 4 No
Frequency of contact between producers and consumers.	13 every cycle,3 every other cycle,6 never	4 every cycle,4 every other cycle,2 never
For what purpose do you communicate?	6 problem with product, 4 special request, 8 questions about product	7 questions about product, 4 special requests
Was this contact satisfactory?	15 Yes, 1 No	9 Yes, 1 No
Have you met any food hub vendors / consumer in person?	17 Yes, 5 No	9 Yes, 1 No
Have you purchased / sold product to a food hub member outside the food hub?	16 Yes, 6 No	7 Yes, 2 No
If problem with a product, do you contact / are contacted by the producer directly?	12 Yes, 10 No	6 Yes, 2 No
Strength the relationship you have with the food hub vendor / consumer [means (standard deviations)]	2.6 (1.4)	3.1 (1.5)

Online Exposure. All of the consumers surveyed felt that there was sufficient information provided by the food hub website to support purchasing decisions. The majority of consumers (19 of 22) felt that the vendor profiles were important to their purchasing decisions, and rated their level of trust in the information provided as very high (mean=4.7, SD=0.5). The majority of consumers (17 of 22) and producers (6 of 11) noted the importance of good food production practices with regard to purchase likelihood. Additionally, locally-sourced foods/ foods miles were found to be important.

Values. The results of the hierarchical clustering of 22 consumers based on the 14 values questions (see Table 1) revealed four clusters (see Figure 2). The authors compared the cluster membership to the answer data to detect whether the clusters represented meaningful patterns in the context of our domain.

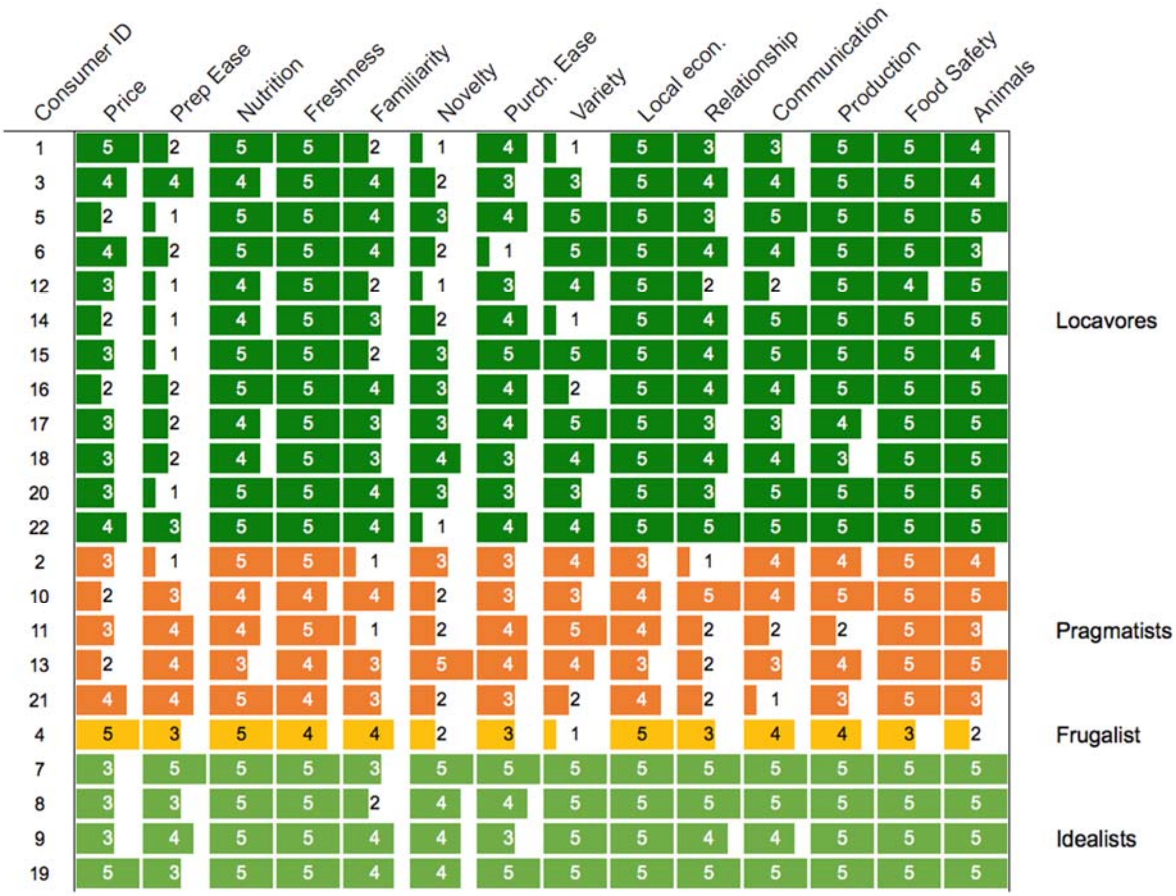

Figure 2: Consumers divided into four clusters based on answers to 14 value questions. Each cell's bar size (i.e., colored region) represents the ratings 1-5, and the bars are colored according to the cluster.

There were with 12 consumers in Cluster 1 (dark green), labeled "Locavores," for whom supporting the local economy and obtaining the freshest food possible are of the highest importance. They also highly value food production practices and the humane treatment of animals, as well as food safety and nutritional content. While these consumers like the idea of having a connection with their producers, it is not a top priority for them. They are only somewhat sensitive to price, and they enjoy spending time cooking and preparing food, so a food's convenience is unimportant to them. Survey participants who were identified as "Locavores" made comments such as "how close my food is produced is a factor for me" and "supporting small/family operations is good for the local economy."

There were with five consumers in Cluster 2 (orange), labeled "Pragmatists." They value food safety, freshness, and nutritional content very highly, but they tend to take a moderate view on the other food attributes. From the points of view of the producers and the food hub manager, the Pragmatists could perhaps be considered the most reasonable consumers – they do not mind paying higher prices for fresh local food, and they do not feel the need to be in frequent contact with producers (i.e., making complaints and/or special requests). Survey participants who were identified as "Pragmatists" were generally less expressive than other groups with comments such as "I wish the food hub had better pick-up hours" and "I would shop here (the food hub) more if it was run more like a grocery."

There was one single consumer in Cluster 3 (blue), labeled "Frugalist," for whom price is of the utmost importance. While clustering was relatively tight, Cluster 3 was a clear outlier. The nutritional quality of food and supporting the local economy are equally important and are the principal motivators for this type of consumer to shop at a regional food hub. Neither food variety nor the treatment of animals is a concern for the Frugalist. The survey participant who was identified as a "Frugalist" is quoted as saying "the 15% fee on the producer and the 15% fee on the consumer side are hard to justify."

Finally, there were four consumers in Cluster 4 (light green), labeled “Idealists,” who feel strongly about these values across the board. Clusters 1 and 4 were closer to each other than Cluster 2. They feel that innate food characteristics (e.g., nutrition and freshness) are extremely important, but they equally support the use of good production practices, the humane treatment of animals, and the health of the local economy. The Idealists are somewhat less concerned with price and convenience, but even these qualities are valued moderately. They tend to be highly supportive of local food systems in general, but they also may have high expectations of the producers and the food hub. Survey participants who were identified as “Idealist” made comments such as “Sustainable production is important to all of us” and “I won’t buy from a producer unless they are transparent on the handling of their animals.”

Producers were more economically driven than previously believed. When asked about motivations to sell to and interact with the food hub the most prevalent response across categories was related to concerns about overhead costs and to a lesser extend ease/convenience of distribution. Many of the producers relied on alternative outlets for the sale of their products and as such were capable of abandoning the food hub should conditions deteriorate.

Discussion

Consumers overall were very values-driven, and the focus of those values fell into a number of distinctive groupings. Few respondents mentioned issues related to price, but those who did so repeatedly mentioned aspects of cost, quantity, and comparisons to classical retail food centers. Yet another strong trend was that of individuals who mentioned food production practices. Respondents often mentioned specific practice techniques (e.g., no GMO, no chemicals, free range, grass fed); persons in this group nearly always responded that these attributes were very to extremely important to them.

A similar trend was observed among individuals who appeared to strongly value sustainability, in terms of local food production and distribution (mentioned by some as “food miles”). These individuals were invariably concerned with food system practices but often would comingle the concept of sustainable production with local production. For example, one respondent consistently would mention the ability to personally check on operations and how that ability was “the only way to be sure they are really organic.”

Agent-Based Model of a Food Hub

An agent-based model of the regional food distribution system was developed in NetLogo (v. 5.0.2) to gain insight into the impacts of various parameters on the overall success of an intermediated regional food supply network. Success was measured by: 1) the total amount of commerce facilitated by the food hub, and 2) the total number of producers and consumers participating in the network over time

The model contains *producer* and *consumer* agents that trade six different categories of food, using the food hub as an intermediary. It is assumed that a producer agent only provides items in a single category, which is typically case in the real regional food system and is supported by the producers’ interviews. The categories and percentage of producers supplying them were: meat (25%), dairy (5%), eggs (9%), fresh produce (36%), ingredients (3%), and processed convenience foods (22%). Each time the model generates a producer agent, there is a fixed probability that the agent will be assigned to particular category (e.g., there is a 25% chance that it will be a meat producer), based on historical data from the real-life food hub.

In this model, the food hub is not represented explicitly as an agent, but rather operates in the background (as it does in real life). Each simulated time-step represents a distribution cycle by the food hub, which occurs every two weeks throughout the main growing seasons (i.e., spring, summer, and fall) and every three weeks in the winter, for a total of 22 cycles per year. Producers and consumers can be in one of three different membership states with respect to the food hub: non-member, member, or canceled member. Agent interactions in this model are confined to producer-consumer transactions (i.e., sales of products from producers to consumers). It is assumed that consumers do not interact/communicate with one another directly, and neither do producers.

Producer Agents

Producer agents are characterized by eleven parameters (Table 5), which govern how the agent is evaluated by consumers and/or how it makes decisions. The numbers assigned to a producer for each parameter represent innate characteristics that are fixed throughout the duration of the simulation run. Each producer is assigned one of three different production capacity levels per distribution cycle. This capacity, which is deterministic and uniform across all six product categories, is defined as the maximum number of units that a producer will sell through the food hub. Producers are also assigned a threshold for the amount of unsold inventory that they will tolerate in each distribution cycle (70%, 80%, or 90%) before they take action by reducing the amount of food they allocate to the food hub in the next cycle. Producers are also characterized by a price parameter (low, medium, or high) indicating its prices relative to other food hub producers. The distribution of producer agents at each price level (i.e., the "Probability" in Table 5) is based on historical data on food producers that sell through the food hub that we studied. Values for food preparation ease and nutritional content are assigned to producers based on the category of food that they produce. For example, most producers of convenience food will have either medium/high values for ease of food preparation, and most producers of fresh produce will have medium/high values for nutritional content. The values for preparation ease, nutritional content, food freshness, and food safety were based on assumptions, since data for these values was not available from the food hub's historical records or the data gathered via interviews.

Table 5. Producer agent parameters.

Producer Parameter	Possible Values	Probability	Distribution Basis	Utility Values
Maximum Production Capacity	50 units/cycle	0.50	System Data	N/A
	100 units/cycle	0.25		
	150 units/cycle	0.25		
Remaining Inventory Threshold	70%	0.33	Assumption	N/A
	80%	0.33		
	90%	0.33		
Price	low	varies based on food category	System Data	1.00
	medium			0.50
	high			0.25
Ease Of Food Preparation	low	0.25 or 0.50: based on food category	Assumption	0.25
	medium			0.50
	high			1.00
Food Nutritional Content	low	0.25 or 0.50: based on food category	Assumption	0.25
	medium			0.50
	high			1.00
Food Freshness Issues	1% chance	0.75	Assumption	# issues / total # transactions
	5% chance	0.25		
Distance From Food Hub	≤ 20 miles	0.70	System Data	1.00
	20-40 miles	0.19		0.50
	> 40 miles	0.11		0.25
Reliability Issues	1% chance	0.90	Assumption	0.01
	5% chance	0.10		0.05
Production Practices	insufficient information	varies based on input data	System Data	0.10
	conventional			0.20
	chemical-free			0.80
	certified organic			1.00
Food Safety Issues	0.1% chance	0.75	Assumption	# issues / total # transactions
	0.5% chance	0.25		
Treatment Of Animals	no certification	varies based on input data	System Data	0.50
	certified humane			1.00

A producer's distance from the food hub may be low (at most 20 miles), medium (21 to 40 miles), or high (greater than 40 miles). The probability that the model will generate a producer agent in any one of these categories is based on the distribution of geographic distances of producers for the real-life food hub: low (70%), medium (19%), high (11%). Each producer is also assigned a probability of failing to provide sufficient reliability to their consumers (i.e., they are not responsive to consumer complaints and/or special requests). Interviews determined that food hub producers are generally very reliable. It is assumed in the model that 90% of producers will rarely fail (1%) to be reliable, while 10% present a slightly higher risk (5%).

Food production practices were divided into four categories, based on the interviews: insufficient information (i.e., the producer did not provide enough detail in its website profile to explain its practices), conventional (e.g., toxic chemical pesticides applied to the crop), chemical-free (i.e., not certified organic but claims that no toxic or chemical inputs used), and certified organic. Based on food hub data, most producers fall into the "chemical-free" category, relying on consumers to trust this claim without any formal certification, although many fresh produce farmers (36%) and ingredient producers (24%) are certified organic. Based on their website profiles, none of the food hub producers of animal-based products use conventional (i.e., inhumane) methods to raise their livestock; however, few were actually "certified humane:" 5%, 10%, and 14% of meat, dairy, and egg producers, respectively.

The utility values associated with each of the producer parameters (shown in Table 5) were not developed from empirical data; however, their relative values are informed by general knowledge of consumer preferences gained via the interviews with food hub consumers. Utility values provide a measure of consumer satisfaction and are scaled from zero to one, with zero being the least-preferred value and one the most-preferred. The direction of preference for these utility distributions tends to be intuitive; for instance, consumers prefer low prices and highly nutritious/fresh/safe food.

Producers are also characterized by several state variables, which may update in each distribution cycle: total number of transactions with each consumer agent, total number of problematic transactions with each consumer, and membership status with the food hub (non-member, member, or canceled member). It is assumed that a producer will offer products for sale through the food hub in every distribution cycle in which it has member status; if the producer cancels its membership, it is assumed to be permanently inactive. A producer's current inventory level is replenished at the start of each distribution cycle and is reduced as the producer sells products to consumers. The level to which the inventory is replenished depends upon the percentage of the producer's capacity that it has allocated to the food hub in the current distribution cycle.

Consumer Agents

Each consumer agent is assigned a demand category, which describes its level of demand (low, medium, or high) for each of the six product categories in each distribution cycle (see Table 6). The probability that the model generates a consumer agent in any given demand category was determined via food hub historical data, which indicated that many (47%) of its participating consumer members were relatively low-volume customers. In the model, this demand is assumed to be deterministic and is constant in each cycle. Each consumer is also assigned to categories that represent its likelihood of being familiar with a food or finding a food to be "novel" in a given interaction with a producer: 50% of consumers will find 5% of food interactions to yield foods that are unfamiliar/particularly novel to them, and the other 50% will encounter unfamiliar/novel foods in 10% of their interactions. For consumers who prefer familiar foods, the encounters with unfamiliar food will reduce their overall appraisal of the producer who provides it. In contrast, for consumers who prefer novel foods, this type of encounter will increase its rating of a producer.

Table 6. Consumer demand categories

Consumer Demand Category	Probability	Demand per Product Category (units/cycle)					
		Meat	Dairy	Eggs	Produce	Ingredients	convenience foods
low	0.47	5	5	5	5	5	5
medium	0.39	10	10	10	10	10	10
high	0.14	20	20	20	20	20	20

To capture such preferences, each consumer is assigned to one of the four different personas, which define the consumer's preferences with respect to producer and food hub parameters. The average Likert value from the human subject data was established for each of the 14 values for each of the four personas. Each of these values was scaled from 0 to 1 (see Table 7).

Table 7. Scaled preferences for each persona and value

Value / Persona	Variety	Buy Convenience	Price	Preparation Convenience	Nutrition	Freshness	Familiarity	Novelty	Distance	Relationship	Reliability	Production	Safety	Treatment Of Animals
Locavore	.700	.700	.633	.367	.917	1.0	.650	.467	1.0	.717	.817	.950	.983	.917
Pragmatist	.720	.680	.560	.640	.840	.880	.480	.560	.720	.480	.560	.720	1.0	.800
Frugalist	.200	.600	1.0	.600	1.0	.800	.800	.400	1.0	.600	.800	.800	.600	.400
Idealist	1.0	.860	.700	.750	1.0	1.0	.650	.850	1.0	.950	.950	1.0	1.0	1.0

Based on the results of Study 1, the probability of the generation of a consumer agent having a given persona in the model was 54%, 23%, 5%, and 18% for being Locavores, Pragmatists, Frugalists, and Idealists, respectively.

Consumer agents have a membership status with the food hub (non-member, member, or canceled member). However, unlike producers, a consumer with member status may decide not to participate in purchasing from the food hub in any given distribution cycle, based on its relative satisfaction with the food hub's performance. This level of satisfaction is measured by its overall utility. The higher a consumer's overall utility value is, the more likely the agent is to engage in commerce with the food hub in a given cycle. This utility depends upon the variety of different products available through the food hub (i.e., the number of producers offering food in each of the food categories, where more producers is equivalent to greater variety, and greater variety is always preferred to less variety), the collective performance of the producer agents (i.e., number of reliability, freshness, and safety incidents) over time, and the percentage of the consumer's demand which can be successfully filled through the food hub in each cycle.

As a consumer successfully purchases items from producers in each cycle, the consumer's demand for that item is reduced. It is assumed that demand that goes unfilled by the food hub will be filled by other exogenous sources (i.e., there is no demand backlog from one time-step to the next). After a consumer completes a transaction with a producer, it will update any variable values (i.e., reliability, freshness, safety, strength of relationship, familiarity/novelty of food product offerings) in its producer ratings vector for that producer. Other components of this ratings vector (e.g., price, distance from food hub) are fixed for a given producer.

Agent-Based Food Hub Model Overview

The ABM consists of five major sub-models: initialization, consumer purchase decisions, consumer evaluation and status update, producer evaluation and status update, and food hub membership update. The initialization sub-model is only run once, at the start of each simulation run. The other four sub-models are executed sequentially in every time-step (i.e., distribution cycle). The details of each of the main activities that occur in each of these sub-models is described in this section.

Initialization. At the start of each simulation run, the model is initialized to set the initial values of the parameters and state variables. A predetermined number of consumer and producer agents are created in this sub-model, each of which is assigned attribute values based on the probabilities given in Table 5. Consumer overall utility is initialized to 1.00 (the maximum value), and food hub membership status for all consumers and producers is set to "member".

Consumer Purchase Decisions. Each consumer who is currently a food hub member checks its overall utility value: if the value is greater than 0.70, then the consumer decides to participate in purchasing; if the value is less than 0.70, the probability that the consumer decides to participate corresponds to its utility value. If it decides to purchase from the food hub, it is assumed that it will try to fill as much as its demand as possible via the food hub. Consumers who have decided to participate are selected in random order to make their purchases from participating producers. Each consumer first assesses its demand in each product category. Then, it seeks out producers that have inventory available in each product category. If the consumer is unable to find any producers with inventory in a product category, its overall utility will be reduced by 0.05, and it will move on to the next category. If the consumer finds a producer(s) with inventory, but this inventory is insufficient to completely fill its demand, its utility will be reduced by 0.01. If the consumer's demand is completely satisfied, its utility will increase by 0.01.

The consumer will then assess each of the available producers with respect to its values, using the producer ratings vectors. It then ranks each of these producers by the total value it provides and selects the producer with the highest rank and purchases either enough of the producer's inventory to fill its demand or all of the producer's inventory (whichever is smaller). If it has any unfilled demand, it will move on to the next ranked producer and will purchase as much food as available/needed, and so on. After each interaction with a producer, the consumer will update its producer ratings vector for that producer. The consumer will continue this process for each of the remaining five product categories.

Consumer Evaluation and Status Update. After all consumer agents have made all of their purchases, each consumer will next evaluate its overall utility with the food hub, which is based on its previous transactions. If a consumer's overall utility falls below a threshold value of 0.10 (out of 1.00), or if the consumer observes that it has participated with the food hub fewer than four times out of the previous eleven distribution cycles, it will change its membership status to "canceled member" and will no longer participate in transactions with the food hub.

Producer Evaluation and Status Update. A producer makes one key decision in each distribution cycle: what percentage of its production capacity to sell to consumers via the food hub (rather than to other market channels, such as farmers' markets). This can vary over time, according to how well the producer's products have sold through the food hub in previous distribution cycles. The producer's degree of participation with the food hub depends on the producer's upper threshold for unsold inventory ratios: the amount of inventory (in food units) left at the end of a cycle, divided by the total number of units that it offered at the beginning of the cycle. If this ratio is equal to zero (i.e., sold entire available inventory), then in the next cycle the producer will increase its offerings by 10% (up to its capacity). If this ratio is greater than the producer's upper threshold, the producer will reduce the percentage of capacity that it offers through the food hub in the next time-step based on actual sales history. If the ratio is greater than zero but less than the upper threshold value, the percentage of capacity in the next time-step will remain unchanged. If a producer's participation drops to less than 10% of its capacity at any point in time, that producer will no longer participate with the food hub (status becomes "canceled member").

Food Hub Membership Update. In each cycle, new producer and consumer agents are generated and initialized as food hub members. New consumer agents are created at a constant rate of two consumers per cycle. A new producer agent is created in every other cycle, on average. These rates are based on food hub historical data.

Study 2: Comparison of Data-Driven Personas with Traditional Consumer Profiles

The agent-based model structure was informed by the knowledge elicitation results and historical data from the food hub studied, both in the development of the modeling dimensions and the distribution and weights given to consumer personas. This is in contrast to the more traditional assumptions that all consumers place and equal and high importance on the core sets of values discussed previously. Thus the utility of the ABM approach can be seen by comparing the ABM outputs (driven by data-driven personas) with a "generic" model that assumes one type of consumer. This first experiment makes this comparison with the goal of demonstrating that the ABM model yields different results, for two different sized food hub systems.

Methods

Independent Variables. There were two independent variables: *Consumer Profile* (Personas vs. Baseline) and *Food Hub Maturity* (Startup vs. Established).

The Personas condition of Consumer Profile uses the four personas derived from the knowledge elicitation study. The Baseline condition assumes that all consumer agents were identical with respect to the 14 values, giving full weight (5 out of 5, on a Likert scale) to every value. Although there is existing research that establishes different preferences for some of these values for farmer's market consumers (Brown, 2002), we are unaware of any research that provides this type of information for regional food hub consumers. As such, the Baseline condition presumes that all 14 values are equally important for regional food hub consumers.

Food-Hub Maturity is distinguished by the initial number of producers and consumers. The Startup condition contains relatively few consumers (100) and producers (30) in the system at the start of the simulation. The Established condition starts the simulation with many consumers and producers (300 and 100, respectively). These numbers were based on a national food hub survey (Fisher, Hamm, Pirog, Farbaman & Kiraly, 2013)

Dependent Variables. There were three dependent variables: 1) quantity of food traded, 2) number of participating consumers, and 3) number of participating producers. Output data was captured at the end of each time-step of the simulation.

Experiment Design. Each simulation was run for 110 time-steps (i.e., distribution cycles). The real-life food hub facilitates 22 distribution cycles per year, so this simulation run length represents 5 years of operation, which is sufficient to evaluate the long-term behavior of the system under different conditions. The model was run for 10 replications under each experimental condition, and the average output values over the 10 replications were used for analysis. Two-sided t-tests were performed to assess whether the Baseline and Persona conditions for both the Startup and Established Food Hubs were significantly different at the last time-step (representing the end of Year 5 of the simulation).

Results

Quantity of Food Traded. For the Startup condition, the quantity of food traded in the last time-step was significantly different ($t_{17}=-2.34, p<.032$) between the Baseline (18,263 food units) and Persona (22,230 food units) conditions (see Figure 3). In the Established Food Hub condition, the quantity of food traded in the last time-step was not significantly different between the Baseline (46,160 food units) and Persona (50,467 food units) conditions.

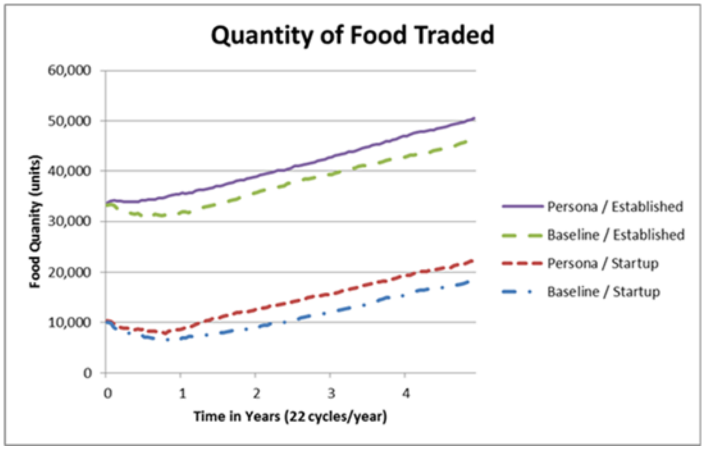

Figure 3. Quantity of food units traded over 5 years of times steps (110 time-steps total).

Number of Participating Consumers. For the Startup condition, the number of participating consumers in the last time-step was significantly different ($t_{17}=-2.68, p<.015$) between the Baseline (13) and Persona (171) conditions (see Figure 4). However, in the Established Food Hub condition, the number of participating consumers in the last time-step was not significantly different between the Baseline (384) and Persona (427) conditions.

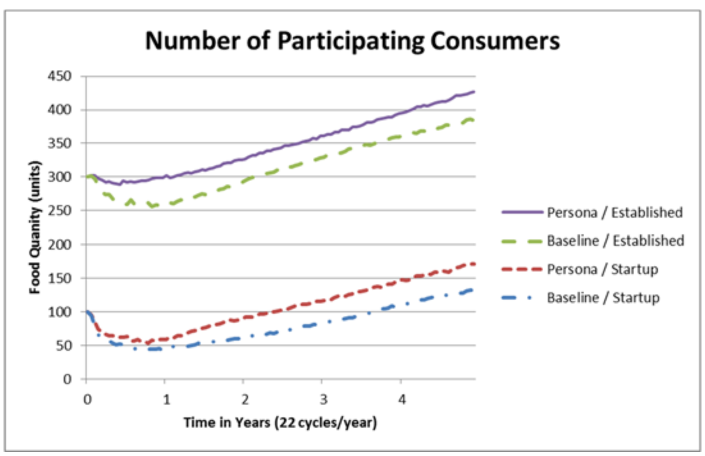

Figure 4. Number of participating consumers over 5 years of times steps (110 time-steps total) for both a startup and an established food hub, using a baseline or Persona-based profile of the consumer.

Number of Participating Producers. For the Startup condition, the number of participating producers in the last time-step was not significantly different between the Baseline

(57) and Persona (63) conditions. Likewise, in the Established Food Hub condition, the number of participating producers in the last time-step was not significantly different between the Baseline (128) and Persona (138) conditions. Figure 5 depicts the results over the four combinations of the independent variables.

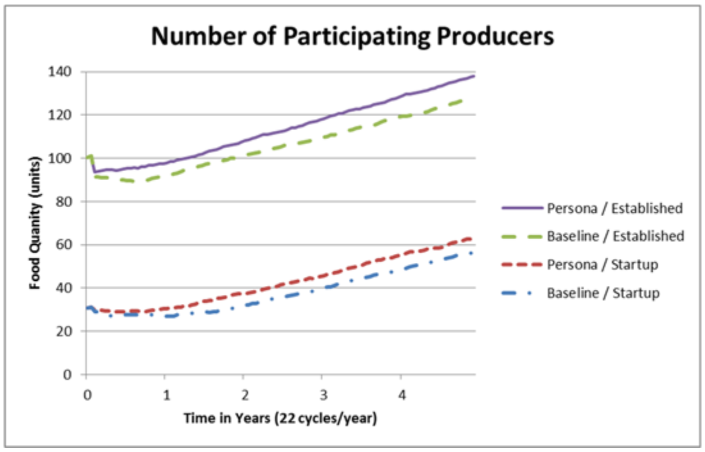

Figure 5. Number of participating producers over 5 years of times steps (110 time-steps total) for both a startup and an established food hub, using a baseline or Persona-based profile of the consumer.

Discussion

The system in Persona-based profile of consumers seems to be more resilient than the Baseline consumer profile. When consumers are more forgiving on certain values (i.e., many are willing to pay higher prices to fulfill other values), the system can survive even when the supply is not perfectly addressing all values. In contrast, in the Baseline consumer profile, all consumer agents want everything to be perfect, so when this expectation is not met, more consumers drop out. This is especially true in the initial stages, when there may not be enough producers of every variety to meet everyone's needs. Although the system was not shown to fail entirely in any of the experiments, the system in the Baseline model took a bigger hit on commerce and participation and took longer to recover, compared with the Persona-based simulations.

Study 3: Change in Producer Reliability

During the knowledge elicitation study it became clear that consumer trust of producers was high. If a producer was a member of the food hub, consumers assumed the producer was reliable. Thus we wanted to explore what would happen to the food hub if reliability was reduced.

Method

Independent Variable. The reliability (high, low) of producers was varied. In the high reliability condition, 25% of producers had a 5% chance of providing unsatisfactory food (the other 75% of producers was assumed to be 100% reliable). In the low reliability condition, the chance of providing unsatisfactory food was increased to 50% for the 25% of producers who had a non-zero chance of being unreliable.

Dependent Variables. There were three dependent variables: 1) quantity of food traded, 2) number of participating consumers, and 3) number of participating producers..

Experiment Design. The simulation was run for a total of 110 time-steps (i.e., 5 years, with 22 distribution cycles/year). The model was run for 10 replications under each experimental condition, and the average output values over the 10 replications were used for analysis. The ABM was run under the same assumptions as described in the ABM description section, using Persona profiles, two consumers join in each cycle, and a 50% probability that a producer will join in each cycle. Two-sided t-tests were performed to assess whether the low and high conditions were significantly different at the last time-step (representing the end of year 5 of the simulation). Initial conditions were set at 100 consumers and 30 producers.

Results

Quantity of Food Traded. The quantity of food traded in the last time-step was not significantly different ($t_{14}=-1.88$, $p<.076$) between the low reliability (18,395 food units) and high reliability (22,229 food units) conditions. Figure 6 depicts the 10 replications for the low reliability (left) and high reliability (right) conditions.

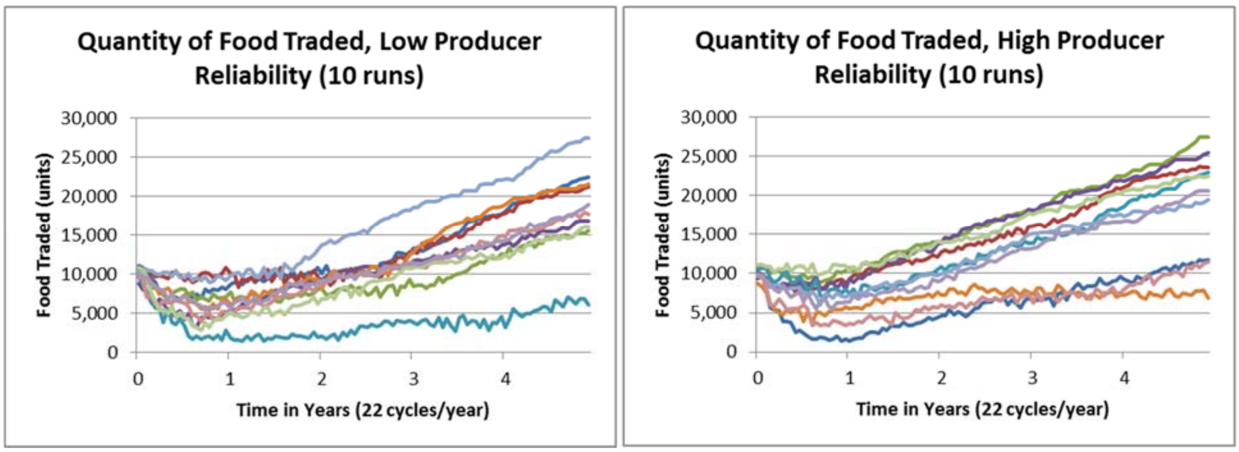

Figure 6. 10 ABM output runs for each of the low and high reliability conditions.

Number of Participating Consumers. The number of participating consumers in the last time-step was significantly different ($t_{15}=-2.26$, $p<.039$) between the low reliability (135) and high reliability (171) conditions.

Number of Participating Producers. The number of participating producers in the last time-step was not significantly different ($t_{15}=-1.95$, $p<.067$) between the low reliability (53) and high reliability (63) conditions.

Discussion

Reduced producer reliability (even when only 25% of producers are reliable 50% of the time) significantly reduces quantity of food traded and number of participating consumers and producers. In one of the replications with low reliability, the system never seemed to recover –

the quantity sold did not increase much over the run, even though new producers and consumers were being introduced into the system in every time-step.

Study 4: Change in Consumer Distribution

The food hub participating in Study 1 was considering concentrating more on price and convenience by offering home delivery of products with a reasonable price that would be subsidized by economies of larger quantities of sale. That led to a discussion of the type of new customers that might be attracted by this change, and the effect on the existing customer profile. Thus we wanted to examine the effects of changing the distribution of consumer agent personas.

Method

Independent Variable. The initial distribution of personas in the customer base (current, Frugalist-focused) was varied. The current case uses the distribution of personas as described in the ABM description section. For the Frugalist-focused condition, the probability that a consumer agent would be generated with Frugalist (i.e., a more price-conscious persona) was increased from the base case of 5% to 25%. The generation probabilities for the remaining personas were reduced proportionally: 43% Locavore, 18% Pragmatist, and 14% Idealist

Dependent Variables. The change in consumer persona distribution was compared.

Experiment Design. The simulation was run for a total of 110 time-steps (i.e., 5 years, with 22 distribution cycles/year). The model was run for 10 replications under each experimental condition, and the average output values over the 10 replications were used for analysis. The ABM was run under the same assumptions as described in the ABM description, using Persona profiles, two consumers join in each cycle, and a 50% probability that a producer will join in each cycle. Two-sided t-tests were performed to assess whether the change in

Persona distribution were significantly different at the last time-step (representing the end of year 5 of the simulation). The system was initialized with 100 consumers and 30 producers.

Results

Distribution of Customer Personas. After 5 years using the current consumer persona distribution, there was little change from the initial conditions (cycle 0) to the end of year 5 (cycle 110), as illustrated in Figure 7 (left). However, when the initial percentage of the Frugalist is set to 25%, by year 1 the proportion of Frugalists has grown to 55% and remains between 45% and 55% in all subsequent years, as illustrated in Figure 7 (right).

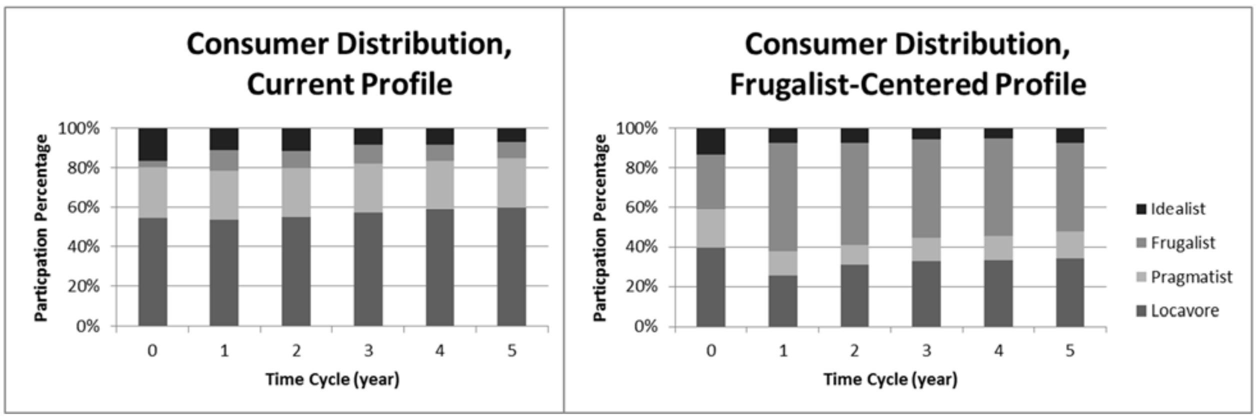

Figure 7. Distribution of consumer personas over time.

Discussion

The outcome shown in Figure 7 was rather unexpected. It is apparent that the distribution of consumers over time is sensitive to the initial distribution of consumer personas. One possible reason for this result is that the Frugalists, while price-conscious, may be generally less discerning than the other personas, such that they are less likely to be disappointed by any given producer and are therefore less likely to stop participating with the food hub. Because they are more easily satisfied, the Frugalists are more resilient than the other consumer personas.

Overall Discussion of Studies 1-4

This research addressed three questions. The first explored the motivational factors influencing food hub members' participation. A primary result of the values data was a cluster analysis that reveals four consumer personas: the Locavores, Pragmatists, Frugalists, and Idealists. These personas and their relative proportions, along with other collected data, were used to develop an agent-based model (ABM) of participation in the food hub. Another notable finding was that consumers and producers had noticeably different profiles from each other in terms of their motivation to participate. The producers were more classically driven, with their decision to participate driven largely by a profit motive, rather than by a values-based motivation that might be expected at a sustainability initiative such as a food hub.

The second research question asked whether a simulation model based on gathered data (Persona-based) would offer noticeably different results than traditional assumptions (Baseline). In Study 2 we found significant differences between the two models, most notably in the startup condition (i.e., a newer and smaller food hub). The Study 2 results suggest that predictions about the success of a nascent food hub would benefit from modeling its consumers in some detail based on their values, since the result would likely be different than one from a traditional model.

The third research question asked what other insights the ABM could reveal about the dynamics of food hub participation. Because Study 1 had revealed that consumers had a high degree of trust in producers, considering them reliable, Study 3 posed the more specific question of how the food hub participation might change if that reliability changed. As predicted, when producer reliability decreased, the model predicted a lower amount of food traded and lower participation. Study 4 was based on the Study 1 finding that only a small proportion of consumers were Frugalists (i.e., someone who is particularly price sensitive). Because the food hub had discussed setting up food delivery with a reasonable price (an approach that would draw a higher percentage of Frugalist consumers), the model was adjusted to explore this option by having a higher probability of Frugalists among the new customer population (25%). This increase led to a stable population of approximately half consumers being Frugalists in the longer term, a result that food hub planners would surely want to anticipate. This result demonstrates the value of modeling based on customer personas.

Conclusions and Future Work

Experimentation with this empirically-informed model yielded statistically significant and usable results, which demonstrate the value of applying human factors techniques and agent-based modeling to the prediction and analysis of sustainability initiatives. The techniques used are not specific to food hubs; the authors anticipate that this approach would be useful for an analysis of many sustainability efforts, especially because it offers a quantitative simulation-based modeling approach for capturing individuals' motivations and values that guide their participation in sustainable initiatives.

In future work, to further model the dynamics of a food hub and to extend our methodology to more complex systems, we plan to interview other food hub stakeholders, including the manager and his employees. Also, it could be valuable to model communications among participants at a finer granularity. Interestingly, while conducting this research, the authors also noted that the food hub's efficiency could be improved by applying other human factors tools, such as task analysis and workload balancing. Finally, it would be useful to apply this approach to a new sustainability initiative to explore whether it is equally valuable in other domains.

Key Points:

- This effort focused on what motivates food producers and consumers to participate in a particular Midwestern food hub. A food hub is an organization that facilitates the distribution of primarily locally grown source-identified food from farmers to customers.
- Based on a series of structured interviews with 29 food hub participants, distinct Personas were developed to characterize the range of consumer values and priorities.
- A predictive model of food hub sustainability was created using human factor knowledge elicitation and agent-based modeling techniques. While previous analyses of food hubs have been primarily financial, the current approach, using the human factors principles of creating a quantitative model grounded in participants' motivations from the field, yields a richer analysis with new insights.
- Multiple simulation studies were conducted to assess the effect of changes in parameters such as reliability or producers and the distribution of consumers to study the long-term effects on food hub sustainability.
- Results suggest that social factors such as desire to support the community are more important than financial factors.

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