The Influence of Culture on the Impact of Recommendations on Product Adoption: A Cross-Cultural Social Network Study

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, Oregon July 29-31, 2007

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Unlike traditional demographic variables that are based on individual characteristics, social network analysis examines the various relationships between people. The basis of network analysis is to understand how actors are located within a network. Self reported data is collected to describe the degree of the knowledge and trust between each pair of participants in this study. Using methods from graph theory the resulting matrices are analyzed resulting in the assignment of degrees of connection among the participants. This research tests whether social networks can be used to predict food product adoption in a multi-country setting. The goal of this paper is to determine if variables that represent different aspects of group structure can better explain why some participants choose to adopt new food products, while others do not.

Social Network Data

Social network data focuses on the relationships between actors. Data is gathered by having actors within a network describe their relationship with other actors of the network. This emphasis on relationships is created by examining how similar or dissimilar the actors are to each other. The typical data matrix in network analysis uses the actors as the headings for both the row and columns of the dataset resulting in a square matrix, with the cells representing the existence or degree of a relationship. The matrix is not necessarily symmetric, as person A may indicate a relationship with person B but person B may not indicate a relationship with A. This type of data allows a more detailed analysis of the relationships between people. Micro-level network analysis focuses on the attributes of the individual within the network. Individual attributes are created by the location of the actor within the structure of the network. At this level of analysis the individuals can be compared within a network.

Because of the nature of network studies a random sample of a larger population is usually not possible. Instead network researchers usually examine some bounded group, such as the employees of a corporation or the students in Marketing 101. This group may or may not represent a sample of a larger population. Thus, when using network data, it is important to realize the limitations a sample may impose on the interpretation of results.

The bulk of research in social networks emphasizes the access to and use of social power. This research sees power as a function of the network itself. Power, in network analysis, is not an absolute characteristic of a person but only exists as a function of the relationships between people. A network that is tightly connected may be more likely to exchange information and resources or may do so at a faster rate, enabling the actors to accomplish tasks that may not be possible in more loosely formed networks. At the individual level power is created by the person's location in a network, relative to others. A simple measure of this power is density, which is the proportion of ties that a person has to all possible ties within a network. As density increases people have greater opportunities and fewer constraints and thus are seen as having a favorable structural position.

Network analysis creates variables that describe different aspects of a person's position within the network. Three of those variables are betweenness centrality, farness, and core membership. Betweenness centrality is a measure of how central a person is within a network. For networks with binary relations, Freeman (1979) created measures of the centrality of individual actors based on their betweenness. Freeman, Borgatti, and White (1991) extended the basic approach to deal with valued relations. Betweenness refers to the number of people that lie "between" two other actors. The higher a betweenness score, the more pairs of people an actor lies between. As an example, a person in a business may want to purchase a large piece of equipment, but first they must get permission for the expenditure. They may not be able to approach the key decision maker directly, instead having to go through intermediaries. The more intermediaries, the more chances for the request to get delayed or turned down. The people who lie "between" the requester and the person with decision making authority have power with respect to the requester. A person who is between more pairs of people has more power over the transmission of information and resources. Therefore, the higher the betweenness centrality score, the more power the actor has within the network.

Farness is the sum of the distance from the actor to all others in the network. Closeness (or nearness) is the reciprocal of farness. People would have a very small farness (a very high closeness) if they were directly connected to everyone else in a network. This position would allow them direct access to information and the ability to directly influence others.

One approach to network analysis is to examine where the group structure of a network begins, and seeks to see how far this kind of close relationship can be extended. Each group starts when two actors are tied together, creating a dyad. A clique extends the dyad by adding to it all actors who are tied to all other actors in the group. This strict definition can be relaxed to include additional nodes that are not quite so tightly tied. Borgatti and Everett (1999) took this idea of groups to its conclusion by dividing the network into a core and periphery. Core members are tightly connected to each other. Periphery members are less connected to each other or to the core members.

Social Network Data, Word of Mouth Referral, and Product Adoption

Word of mouth advertising (WOM) is described as interpersonal interaction that does not involve personal selling. WOM has been documented in marketing research to have a pervasive impact on consumers' behavior (Arndt 1967; Engel, Blackwell and Kegerreis 1969; Richins, 1983) in diffusion of new products and services, however, as stated by Reingen and Kernan (1986), a weakness of the previous research is that it failed to capture the social-structural context of the communication. Reingen and Kernan (1986) argued that the study of informal communication data (i.e. WOM) should include a focus on relational data. In their 1986 paper, they presented an illustration of the application of network methods in a case study of referral behavior. They hypothesized that consumers with multiple potential sources for referral were more likely to be activated if the referral came from a source with a stronger tie. However, they note that previous research by Granovetter (1973) and Weismann (1983) identify a special significance for weak ties as a bridging function enabling referrals to travel from one subgroup to another. Results from a case study examining referral behavior found that the greater the communication frequency and importance attached to the social relation, the more likely the tie was to be activated for the flow of referral. Similarly, within subgroups, importance attached to the social relation was significantly and positively related to the likelihood of referral. A second study was conducted in 1987 to further examine weak ties (Brown and Reingen, 1987). In this paper, they tested and proved the hypothesis that weak ties served as bridges through which word of mouth referrals flowed more often than strong ties. They found while weak ties were important in the flow of word of mouth across groups; strong ties were more likely to be activated for flow of referral information. Brown and Reingen suggest this is a result of more frequent interaction with strong ties. However, weak ties were more often solicited for information, possibly due to the circumstances under which information flows.

Suarez (2005) examined the impact of strong ties in adoption in the wireless telecommunications industry. Suarez notes that in industrial economics literature, most studies use total network size as a measure of strength, regardless of characteristics of the user base. He hypothesized and showed that strong-tie network effects would be better predictors of choice of technology. In his case, he found that cellular operators tended to pay more attention to decisions made previously by other operators in a selected subset of countries with which they had strong ties than to others.

In one of the few cases where network theory has examined product adoption in the agricultural field, Boahene, Snijders, and Folmer (1999) sought to address the question of whether the economic situation of farmers adopting a new technology was more important than their social networks. They stated that farmers were assumed to make adoption decisions with an objective of utility maximization. In addition to factors like income, land, and labor, they included measures of information, obtained both from extension specialists and social networks. While they found a negative relationship between visits from extension agents and adoption, they found the number of previously successful adopters in their network was positively related to product adoption. Boahene et al. suggested this indicated a substitution of information acquired from their social network for information obtained from extension agents. Their research also indicated smaller farmers benefited more from information from their networks.

Data

The data for this study were obtained through two web-based surveys of undergraduate students. One was conducted with students enrolled in a senior-level course in the Food and Resource Economics Department at the University of Florida (UF). As an upper-level course in a relatively small major (380 total students), the students in this class were highly likely to know each other and have observed the behavior of other class members in previous courses, including group work, as well as in social settings. The second survey was conducted in a second-year course of students in the Food Marketing degree program at the University of Reading (UR). Again, as a relatively small major, these students had worked in groups over an 18 month period.

Of the 41 members of the UF class, 36 participated in the survey and 33 completed the survey for a net response rate of 80%. Of the 39 members of the UR class, 17 participated and completed the survey, for a net response rate of 44%. Due to the sampling method, the sample has limited demographic diversity, though given network studies must analyze related participants, this is not unexpected. Table 1 provides a summary of the demographic characteristics of the participants.

Table 1. Demographic Summary of Respondents.

Variable	US Survey (n=33)	UR Survey (n=17)
Gender		
Percent Female	33.3% (11)	64.7% (11)
Age		
20 or under	6.1% (2)	64.7% (11)
21	9.1% (3)	11.8% (2)
22	27.3% (9)	11.8% (2)
23	30.0% (10)	0% (0)
24	9.1% (3)	0% (0)
25 or older	18.1% (6)	5.9% (1)
Race/Ethnicity		
Caucasian	72.7% (24)	70.6% (12)
African/American or Black	9.1% (3)	5.9% (1)
Hispanic	6.1% (2)	0% (0)
Asian or Pacific Islander	9.1% (3)	5.9% (1)
Pakistani	0% (0)	5.9% (1)
Other	3.0% (1)	11.8% (2)

Participants were first asked to rate how likely they were to try three new food products: a new chocolate bar, a burger at a fast food restaurant, or a meal at a new sit-down restaurant. Results are presented in Table 2. Next, participants were asked to identify how well (if at all), they knew other classmates (names and pictures were provided) in the class on a 5-point scale, with 1 = do not know to 5 = know very well. The results from this set of questions were used to generate a social network matrix**.** For the UF students, of the 1,056 possible pairs (each of the 33 respondents rated the remaining 32 respondents), there were 369 cases where they indicated they at least knew each other. Of those, 61.0% of the cases were rated know very little, 24.4% were rated know, 9.8% were rated know well, and 4.9% were rated know very well. For the UR students, of the 272 possible pairs (each of the 17 respondents rated the remaining 16 respondents), there were 207 cases where they indicated they at least knew each other. Of those, 30.0% of the cases were rated know very little, 43.5% were rated know, 13.0% were rated know well, and 13.5% were rated know very well.

Table 2. Likelihood to Purchase Products Prior to Recommendation

	Definitely	Probably	Might or	Probably	Defiantly

	would not	would not	might not	would	would
UF					
Chocolate Bar	42.4% (14)	21.2% (7)	18.2% (6)	12.1% (4)	6.1% (2)
Burger	21.2% (7)	39.4% (13)	15.2% (5)	15.2% (5)	9.1% (3)
Restaurant	0% (0)	9.1% (3)	33.3% (11)	36.4% (12)	21.2% (7)
UR					
Chocolate Bar	29.4% (5)	29.4% (5)	23.5% (4)	5.9% (1)	11.8% (2)
Burger	52.9% (9)	11.8% (2)	17.6% (3)	17.6% (3)	0% (0)
Restaurant	0% (0)	23.5% (4)	23.5% (4)	41.2% (7)	11.8% (2)

The knowledge matrix is displayed using Netdraw (Borgatti 2002), a social network visualization software, that can create a visual representation of the network using nodes and vectors (Figures 1 and 2). Each node represents a person; each vector or line is a tie between that person and another. The thickness of the line represents the strength of the tie. An arrow head on each side of the line indicates that both people acknowledged that a tie exists. If there is only one arrow head then one person said a tie exists between them and another person while the other person did not say a tie exists.

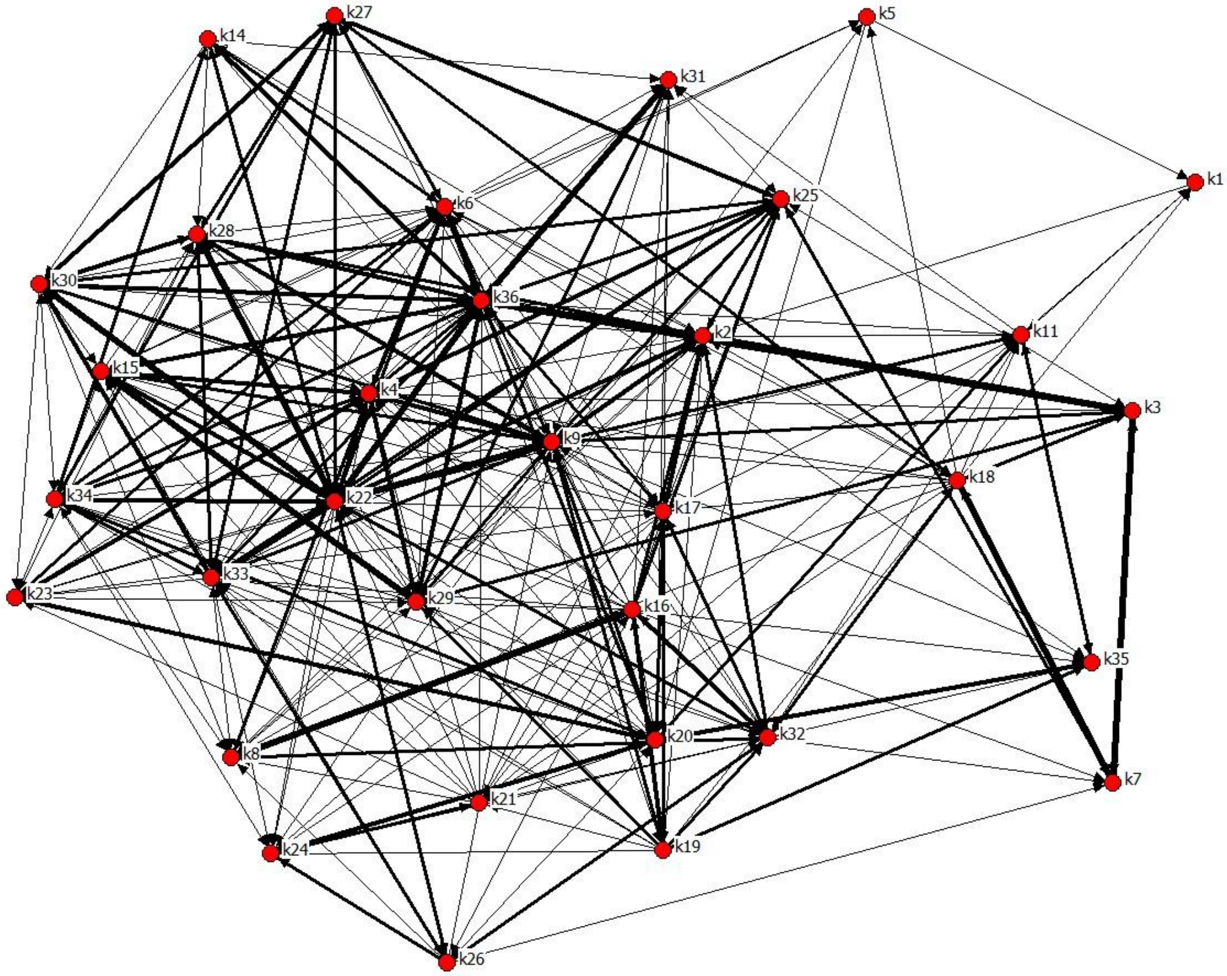

Figure 1. Social Network Graph – UF

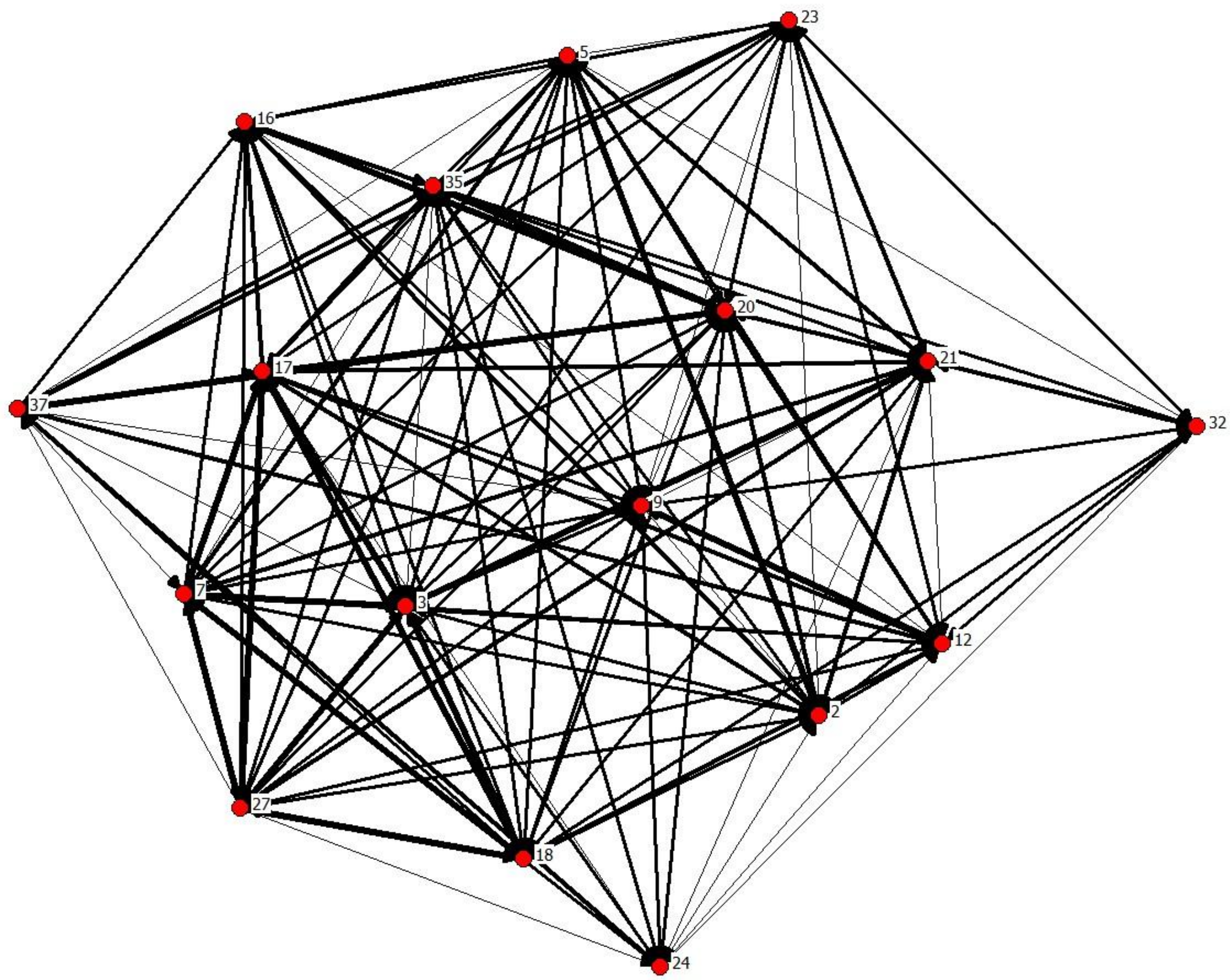

Figure 2. Social Network Graph - UR

Three independent network variables (farness, betweenness and core) were calculated using Ucinet software (Borgatti, Everett et al. 2002). Table 3 lists the basic characteristics of the two continuous variables. Core is a binary variable with a person either being in the core group of students or not. There were eleven people in the core for both networks. Farness and betweenness are also plotted to show the variation within the data (Figures 3 and 4).

Table 3. Characteristics of Continuous Network Variables

	Farness - UF	Farness - UR	Betweenness UF	Betweenness UR
Mean	55.70	19.82	2.39	1.59
Standard Deviation	8.21	2.60	2.36	1.00
Minimum	42	17	0.15	0.45
Maximum	73	26	9.72	3.71

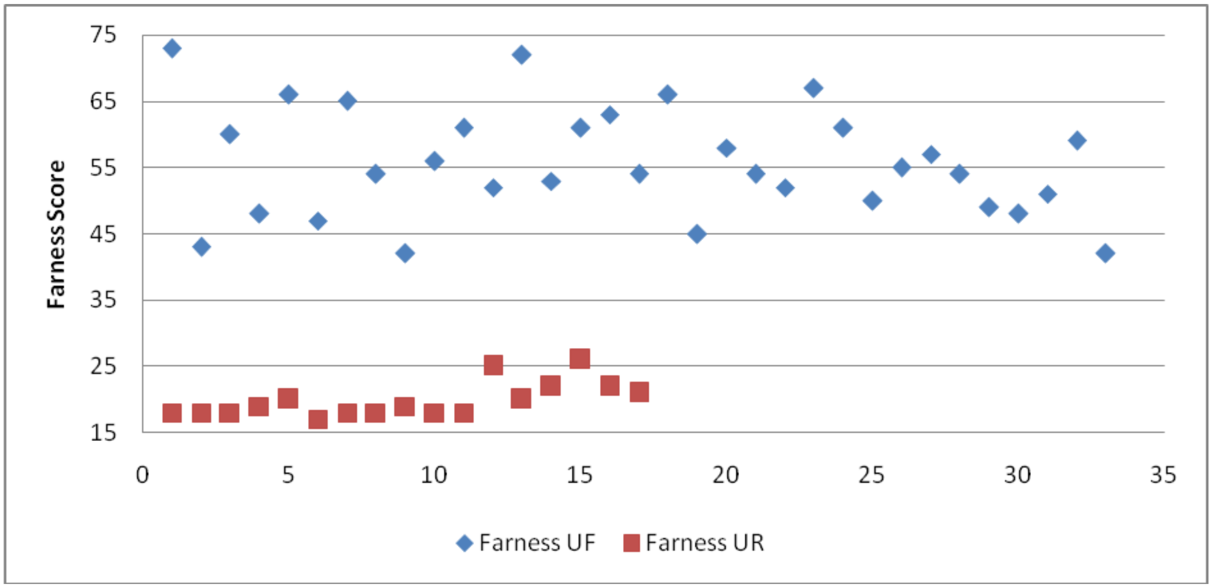

Figure 3. Farness Scatterplot

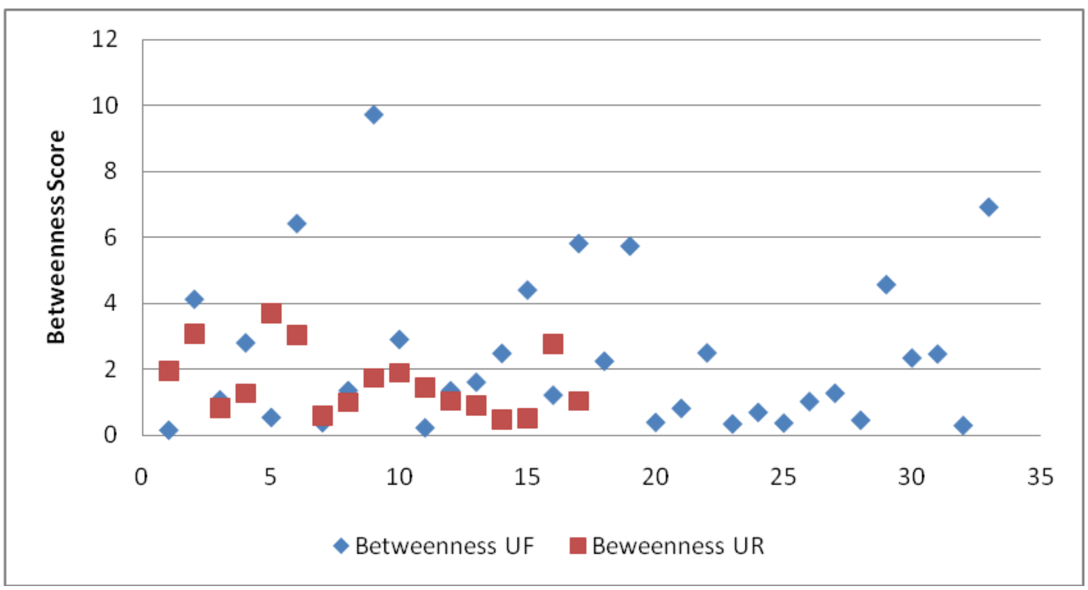

Figure 4. Betweenness Scatterplot

Respondents were then asked how well they trusted each person they knew (on a 5 point scale). Results from this question are displayed in Figure 5. Finally, for each person the respondent at least knew, they were asked the likelihood to purchase the three food products based upon that person's recommendation (they were reminded at this time of their original level of intent to purchase). In most cases for the candy bar and restaurant, the likelihood to purchase either remained the same or increased (Figures 6 and 7). For the sandwich, 28.4% of the respondents decreased their likelihood to purchase based on the recommendation.

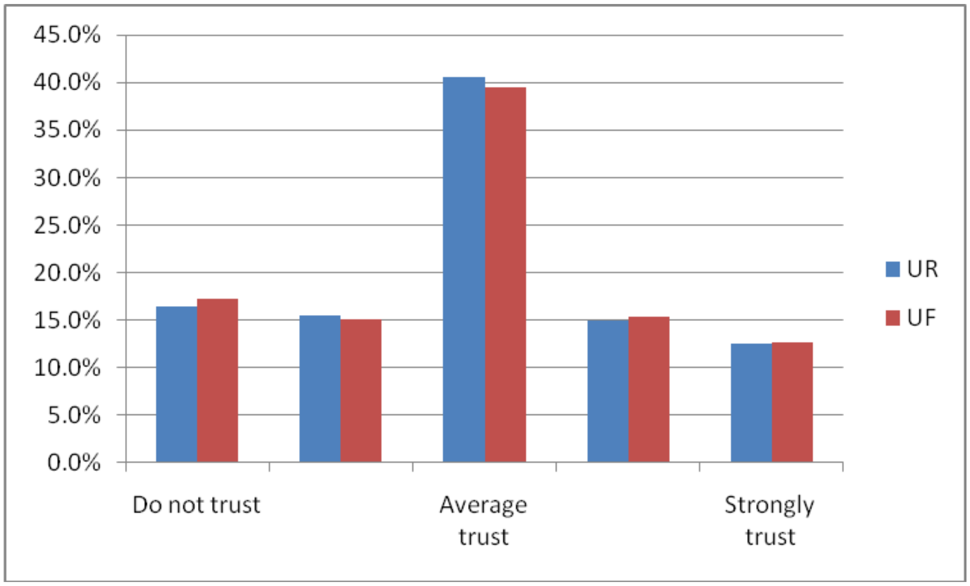

Figure 5. Trust in classmates.

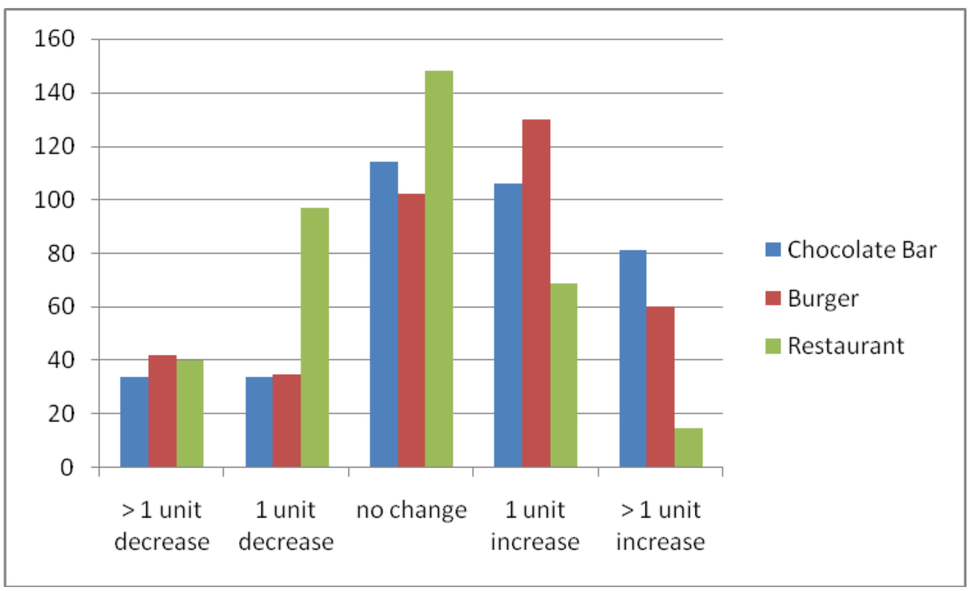

Figure 6. Change in Likelihood to Purchase Product Based on Recommendation, UF

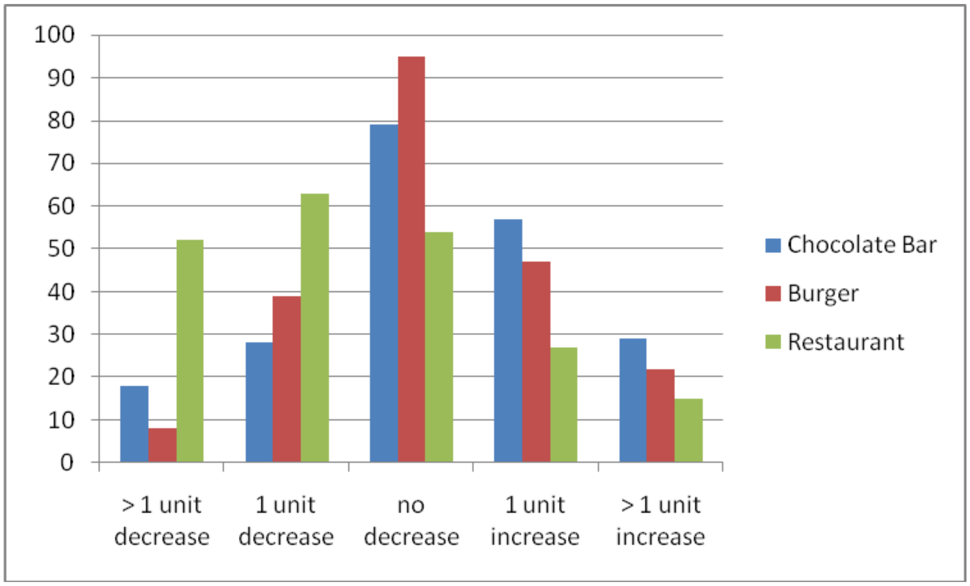

Figure 7. Change in Likelihood to Purchase Product Based on Recommendation, UR

Model and Results

The main goal of this study was to determine if social network variables can be used to enhance our understanding of food product adoption. To test that, two models were run for each of the three products. In all cases, the dependent variable was the difference between the willingness to purchase rating before and after the recommendation. The base model was:

Difference = *f*(trust, age, gender, primary, knowledge dummy variable)

where knowledge was a dummy variable representing how well the respondent knew the referrer, age and gender were the respondent's age and gender, and primary indicated if they were the primary shopper for the household. The second model was:

Difference = *f*(trust, age, gender, primary, own farness, own betweenness, own core, recommender's farness, recommender's betweenness, recommender's core)

where farness, betweenness, and core are the network variables described previously for both the participant and the person recommending the product. Our hypothesis is that the second model will be able to predict behavior more accurately as the inclusion of the network variables will increase the accuracy of the specification of the model.

Ordered probit regressions were run (LIMDEP software package, Version 8.0, Econometric Software Inc, Bellport, NY) as the dependant variable was categorical, with a value of 0 representing a decrease in likelihood to purchase after recommendation by more than one unit, 1 representing a decrease in likelihood to purchase after recommendation by one unit, 2 representing no change in likelihood to purchase after recommendation, 3 representing a one unit increase in likelihood to purchase after recommendation, and 4 representing an increase in likelihood to purchase after recommendation by more than one unit. Results are presented in Table 4. In each of the three cases (chocolate bar, burger, and restaurant), the model with the network variables was more accurate at predicting the dependent variable and network variables were significant in the equations. However, the products did not behave in the same manner.

Table 4. Results from Models

	Chocolate Bar		Burger		Restaurant	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Gender	-0.240**	-0.270***	-0.630***	-0.656***	0.341***	0.361***
Age	0.041***	0.013**	0.067***	0.031***	0.027***	0.020***
Primary	0.274***	-0.046	-0.228**	-0.383***	-0.170*	-0.164
Low Trust	-0.616***	-0.619***	-0.315***	-0.261**	-0.114	-0.011
High Trust	0.214*	0.269**	0.469***	0.587***	0.723***	0.949***
Location	0.475***	-6.265***	0.263**	-5.309***	0.126	-1.539
Low Knowledge	0.314***		0.196*		0.161	
High Knowledge	0.594***		0.530***		0.497*	
Own Betweenness		0.052***		0.018		-0.013
Own Farness		0.024		0.006		-0.045***
Own Core		-0.075		0.030		0.243**
Rec. Betweenness		0.031*		0.047**		0.045**
Rec. Farness		0.036**		0.050***		0.047***
Rec. Core		-0.056		-0.197**		-0.149
Naïve prediction	33.5%	33.5%	34.2%	34.2%	35.1%	35.1%
Model prediction	34.4%	36.6%	34.5%	34.9%	35.6%	41.5%
Log-likelihood	-831.48	-811.65	-788.35	-780.97	-775.57	-761.01

Where ***, **, and * represent significance at the 99%, 95%, and 90% confidence levels.

Though in each case the model with the network variables, the impact of the network variables on each model differs in some aspects. In all three cases, the location of the recommender in the network was significantly important. Respondents were slightly more likely to listen to the recommender's advice if the recommender had a higher farness and a higher betweenness score. This can be interpreted as meaning that as the recommender's network increases in its reach, the more that person's recommendation is listened to. This is consistent with previous literature such as Brown and Reingen (1987) that suggests that weaker links in networks may be a source of word of mouth referral as they may bring "outside" information to the network. In the case of the burger, if the recommender was in the core group, they were less likely to be listened to for a recommendation.

With regards to the own person's location in the network, each model differed. For the chocolate bar, the only significant variable related to the own network was betweenness. This positive relationship indicated that as the person's betweenness score increased (as the actor had higher power), their willingness to listen to recommendations increased. This did not hold true for the burger or restaurant models. For the restaurant, as the person's farness score increased, they were less likely to respond to recommendations, but if they were in the core, they were more likely to respond. The burger model showed no relationship between the own person's position in the network and willingness to listen to recommendations.

It is also important to note that the network descriptors are based on knowledge of other known individuals. Though one might know someone, they may distrust the person, potentially explaining the decreases in willingness to try products. In fact, in the model for each product, trust was significant. For each model, people were more likely to increase their willingness to purchase products from people they trusted more than average. For the chocolate bar and burger, people were likely to decrease their willingness to try the products if they distrusted the recommender. However, distrust did not influence willingness to try the restaurant.

Conclusions

The goal of this project was to conduct a preliminary study to determine if network data could be collected in conjunction with stated willingness to adopt new products and to determine if this data could be used to predict a person's willingness to try a new food product. Undergraduate students from two classes in the U.S. and the U.K. were used as they were likely to know each other well enough to have a network with strong and weak ties, and allowed to examine group structures in two countries. The results from the network analysis were then used in a regression analysis to determine if either the respondent's or the recommender's network position influenced changes in willingness to try new products based upon a recommendation. Three different products were modeled, and the result in all cases was the network variables did improve the predictability of the model. Interestingly, the network variables behaved slightly differently for each product, bringing about the question of why.

Clearly, though knowledge of the person was important, simply using the knowledge variables to predict willingness to try a product based on a recommendation was not satisfactory. Not only did the model barely outperform a naïve prediction, the knowledge variables did not relate to the dependant variable in a predictable manner. In all three models, having both a lower and higher than average knowledge of the recommender was positively related to change in willingness to try the product. Additionally, and more importantly, knowledge of a person doesn't indicate trust. The results from this study showed there was a significant amount of 'distrust' of other members of the network. Trust added to the explanatory power of the model, perhaps explaining the at first counterintuitive result that willingness to try a product after a recommendation was lower than prior to the recommendation.

Finally, location was a significant explanatory variable. Without the network variables, location was positively related to willingness to try a chocolate bar or burger based on a recommendation, indicated students from the U.S. were more likely to listen to recommendations. However, once the network variables were included, students from the U.S. were significantly less likely to listen to recommendations, implying location variable was potentially capturing different network effects.

The results bring about interesting questions for future research in the area. First, as the network variables did explain part of the variation in changes in willingness to try each product, we believe this is an important area for future studies with broader samples and more in-depth surveying. Second, as the network variables did not behave the same across products, it is important that future studies carefully consider what products are studied, and potentially, that a range of products should be included. Finally, given the fact that a number of respondents decreased their willingness to try a new product after receiving a recommendation, the consideration of trust in the network actors is an important component of these studies. In summary, our findings are that there is something to be gained by combining social network theory with product adoption studies.

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