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Role of Social Network on Technology Adoption: Application to Nebraska Producers in the Face of Undesirable Vegetation Transitions

Introduction:

In recent years, the world's physical and biological systems have gone through drastic undesirable transitions affecting aquatic habitat, water resources, and agricultural productivity of rangelands, forests, and other ecosystems (Stefen et al., 2015). Undesirable Vegetation Transitions (VTs) occur in different biomes due to climate change, and anthropogenic activities, such as those involving lack of suitable land management practices. According to a USDA report from 2010, invasive plants have covered half of the non-federal rangelands adding up to more than 50% of the plant cover in 6.6% of these lands. Damage and control costs linked to these invasive species are estimated to cost the global economy $1.4 trillion in losses yearly, which is nearly 5 percent of the global economy. The cost of these damages in the United States is $137 billion annually (Pimentel et al., 2000; Pimentel et al., 2014). The rangelands in the state of Nebraska (NE) face undesirable VTs due to social-ecological interactions (between trees and producers), which are responsible for the shift from grassland to woody plants (Engle et al.,2008). Considering the intensity of damage associated with the VTs, Uden et al. (2019) have developed a screening and imaging tool that links spatial resilience theory with computational techniques to detect undesirable VTs responsible for affecting rangelands' productivity and generated ecosystem services. This new technology, if adopted by producers, could lead to significant environmental improvements on rangelands owing to producers being able to anticipate VTs and taking actions on their operations to apprehend/address them. However, there is limited knowledge regarding the degree to which producers would be willing to adopt any technology in general and this screening tool in particular.

Thus, this paper (using survey data) looks at the issue of producer likelihood to adopt with a focus on Nebraska producers with specific attention to the role of information obtained through their social networks on willingness to adopt. Additionally, we also focus on producer's willingness to seek information about a new technology which is an essential step prior to making a decision to adopt the new technology. We are interested in social networks given the extensive research showing the potential effects of social networking on technology adoption in a variety of contexts such as the adoption of high-yield seed varieties (Foster & Rosenzweig, 1995), a new crop variety (Bandeira & Rasul, 2006), the adoption of pineapple production technology (Colney & Udry, 2004), new groundwater extraction and irrigation techniques (Genius et al., 2013), conservation land management (Kolady et al., 2021) and crop rotation practices (Che et al., 2022), and the limited application of this aspect to study producer decision making with respect to VTs.

Survey Design and Variables:

To examine the effects of social network measures, we developed a survey questionnaire which was fielded to a sample of producers (ranchers and farmers) who own land equal to or greater than 20 acres in selected counties in NE experiencing undesirable VTs due to encroachment of woody plants onto grass dominated land (see Fig. 1). Information identifying potential survey respondents was purchased from the profit company Farm Market ID which curates, cleans, and produces names, addresses, and operation information from the USDA NASS.

The survey included a letter describing the purpose of the survey, IRB approval information, voluntary nature of participation, and statement of confidentiality of the survey responses received. We implemented the Dillman survey administration method (Dillman et al.,2014) in mixed mode (both online and paper) and sent out the survey between June 2021 and July 2021. A total of 570 respondents (out of the 4500 who received the survey) completed and returned the questionnaires. The overall response rate was 13%.

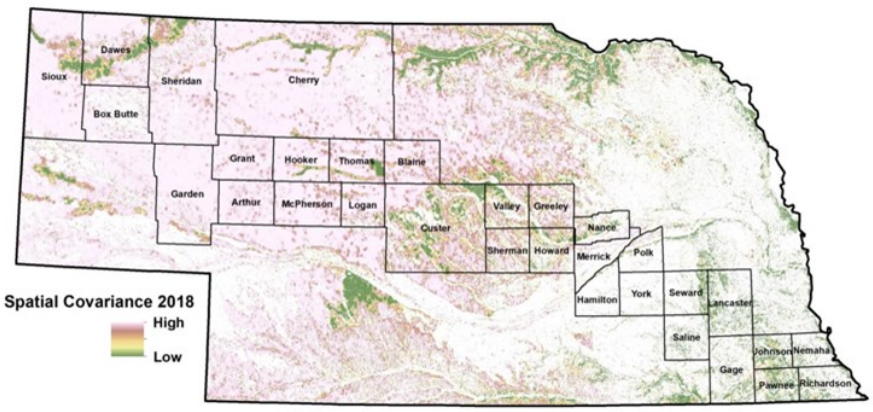

Fig 1. Cross -section of Nebraska counties selected for the survey

The questionnaire included three main sections: *i*) operation (farm and ranch) and producer characteristics, *ii*) attitudinal questions pertaining to VTs, and *iii*) questions focused on identifying the social network of each respondent along with key network-based information variables. In the first section, we included variables *Age, Education, Total acreage, and Intensity of vegetation transitions experienced by the respondent.* We kept *Age* variable as an open-ended question in the survey, *Education* measured the highest level of completed education, categorized using *1 = "less than high school," 2 = "high school,"3 = "some college/technical school," 4 = "4-year college degree,"5 = "Masters' or Doctoral degree."* Variables that capture operation characteristics included the *Total acreage* of owned and rented land. The *Intensity of VTs* within a 10 km radius of the producers' address was measured using geo-spatial data. **Table 1** presents the summary for demographic variables used in the analysis.

We included several questions on *Risk Attitude, Risk Perception, Perception of VTs and Spillover Effects* to assess respondents' attitude towards risk and undesirable VTs, in the second section. We assessed risk perception of respondents regarding VTs based on three different dimensions – threat of VT to ecosystem services, to operation-level profitability, and overall operation productivity. Spillover effect refers to change in a respondent's behavior after observing incidence of VT from the environment around him or leaning about it from his social network. Each question was assessed using five-point Likert-type questions *(1=strongly disagree to 5= strongly agree).*

Social Network Metrics Construction:

To elicit the data on producers' social network, we followed three steps: First, we used a name generator question to identify each respondent's network contacts: (e.g., "Please list the names of people with whom you work on your operation, communicate about your operation, and seek advice for rangeland management and operation). The focus of the analysis of our study was personal networks of each respondent, which is known as an *ego* network. An *ego* network is defined as a segment of a social network formed by an individual, known as ego (Arnaboldi et al., 2016). Going forward, we will use the term *ego* to identify respondents and *alter* to identify the respondents' network contacts. Second, each ego answered several follow-up questions to elicit network composition constituting alters' occupations, length of time each alter was known, frequency of interaction with each alters, and types of information received from each alter.

To estimate the ego's social network measures metrics focusing on *Occupation* Heterogeneity in ego's network*, Information Heterogeneity* measuring the heterogeneous profile of information ego receives from his network, and *Network Efficiency*, *Frequency of Interaction with alters,* and *Ego Network Density* was computed using the E-Net software (Borgatti, 2009). The multiple heterogeneity measures range between 0 and 1 with a value of zero representing receipt of less diverse information from alters and a value of one representing information obtained with highest diversity. To measure the efficiency of the social network structure of each *ego*, we used E- Net to get a measurement on the incidence of *structural holes*. A structural hole is conceptualized as any empty space between two individuals in the social network (Burt, 1992). For our context, to understand whether the information ego gets from his social network is new or redundant it is important to elicit the structural hole efficiency measure of social network structure. E-Net computes structural hole efficiency measure between zero and one with a value "1" implying that the network structure is maximally efficient with there being non-redundancy of information received from alters and a value of zero signifies that the information *ego* gets from his network is not efficient implying presence of structural holes and redundant information.

Table 1. Summary Statistics for Demographic Variables

Demographic/ Socioeconomic Variables	Number of Observations	Mean Value
Age	450	64.81
Education	516	3.7
Income	471	3.50
Gender	M=419, F=42	1
Owned Acreage (Owned)	539	1800.52
(Rented Acreage	427	1073.72

Results:

We have organized our results into a study of general willingness to seek new information followed by a likelihood of adopting the new screening technology. The description of results below focuses on ego's social network measures that have a significant and non-significant impact on dependent variables. Further, the description of the results for attitudinal and demographic variables is only specific to only significant variables.

Table 2 presents the estimates for the willingness to seek information regarding new management practices and technologies using an ordered probit regression analysis. The dependent variable in these regressions is *"willingness to seek information"* that takes integer values between 1 and 5 with 1 representing low willingness and 5 representing high willingness. Results for multiple models are presented which differ on the basis of the inclusion of the social network metrics. We controlled for each social network measure separately due to high multi-collinearity between social network variables, while attitudinal and demographic variables are same in all models.

The estimates for social network variables in each model show that there is no significant relation between each social network measure and the willingness to seek information. However, in models 1, 4, and 5 we observe that individuals with high-risk attitude have higher willingness to acquire information at 5% level of significance. Similarly, the *spillover effect* has a significant positive effect on the willingness to seek information in all five models at 1% level of significance. This provides evidence that when a producer observes the sign of VT on his neighbor's land his willingness to seek information about new technologies and practices which can help him manage his land to mitigate the likelihood of VTs. Moreover, the demographic variable for *education* with a negative and significant effect shows that with increase in the level of education a producer's willingness to seek information decreases.

Results for the likelihood of technology adoption are presented in **Table 3**. The dependent variable for the results of the ordered probit regression is *"likelihood of adopting screening and imaging technology"* and it takes values between 1 to 5 with 1 representing "less likely to adopt screening technology" and 5 representing "more likely to adopt screening technology".

The coefficients for social network measures show that *occupation heterogeneity, frequency of interaction, and network density* has a significant and positive effect on the likelihood of technology adoption at 10%, 5%, and 1% level of significance, respectively. In contrast, the network efficiency measure has a significant and negative effect on the likelihood of technology adoption at 1% level of significance. These results provide evidence that social network composition significantly influences producers' likelihood of adoption of screening technology. However, with increase in the *network effi-*

ciency and exchange of more varied (and hence less redundant) information, the likelihood of screening technology adoption decreases.

The coefficient for the *risk attitude* variable in columns 1, 2, 4, and 5 suggests that producers with higher risk attitudes are more likely to adopt the technology. In addition, the *spillover effect* again leads to a positive significant relation, implying that the effect of observing VTs on neighbor's land increases the producer's likelihood of adopting screening and imaging technology. The estimate for the demographic variable *education* is positive and significant, indicating that producers are more likely to adopt screening and imaging technology, with the higher education estimate for *age* variable is negative and significant, implying that older producers are less willing to adopt the new technology. Finally, the greater the managed acreage, the higher is the producer's likelihood of adopting the screening technology.

The bottom five rows of Table 3 present the results for the interaction effects between risk attitude and each social network measure. For instance, fig 2a shows that with a high-risk attitude, producers having highly efficient networks are less likely to adopt screening technology than producers with low efficient networks. Likewise, fig 2b demonstrates that producers with high risk-attitude and having more frequent interactions with their alters are more likely to adopt screening technology than producers who interact with their alters less frequently.

Table 2. Ordered Probit Regression Estimates for Willingness to Seek Information

	Model 1	Model 2	Model 3	Model 4	Model 5
Occupation Heterogeneity	0.643 (0.705)				
Information Heterogeneity		0.087 (0.720)			
Network Efficiency			-0.181 (0.983)		
Frequency of Interaction				0.816 (0.337)	
Network Density					0.085 (0.750)
Risk Attitude	0.544** (0.236)	0.471* (0.246)	0.229* (0.273)	0.491** (0.207)	0.401** (0.196)
Belief	0.197 (0.240)	0.216 (0.229)	0.022 (0.239)	0.140 (0.229)	0.034 (0.241)
Spillover Effect	0.635*** (0.132)	0.688*** (0.134)	0.680*** (0.137)	0.667*** (0.133)	0.684*** (0.137)
Risk Perception	0.100 (0.077)	0.096 (0.077)	0.103 (0.080)	0.079 (0.075)	0.106 (0.080)
Age	-0.006 (0.007)	-0.004 (0.006)	-0.005 (0.007)	-0.003 (0.006)	-0.005 (0.007)
Education					
College	-0.425 (0.227)	-0.404 (0.216)	-0.480** (0.230)	-0.258 (0.216)	-0.489** (0.231)
Post-Graduate	-0.592** (0.232)	-0.432** (0.220)	-0.509** (0.229)	-0.360 (0.219)	-0.520** (0.230)
Tree Cover	1.649 (2.766)	2.988 (2.637)	2.482 (2.854)	2.183 (2.710)	2.464 (2.856)
Total Land	0.000 (1.29e-05)	6.72E-06 (1.25e-05)	8.97E-06 (1.26e-05)	5.76E-06 (1.25e-05)	8.48E-06 (1.27e-05)
Risk Attitude* Perception of VTs	-0.040 (0.069)	-0.048 (0.066)	0.004 (0.069)	-0.024 (0.066)	0.001 (0.069)
Risk Attitude*Occupation Heterogeneity	-0.154 (0.210)				
Risk Attitude*information Heterogeneity		-0.007 (0.220)			
Risk Attitude*Network Efficiency			0.170 (0.296)		
Risk Attitude*Frequency of Interaction				-0.036 (0.109)	
Risk Attitude*Network Density					-0.124 (0.225)
Number of Observations	256	268	252	268	252

Table 3. Ordered Probit Regression Estimates for The Likelihood of Technology Adoption

	Model 1	Model 2	Model 3	Model 4	Model 5
Occupation Heterogeneity	1.144* (0.642)				
Information Heterogeneity		-0.038 (0632)			
Network Efficiency			-2.595*** (0.872)		
Frequency of Interaction				0.816** (0.337)	
Network Density					1.809*** (0.660)
Information Seeking	0.098 (0.077)	0.107 (0.078)	0.097 (0.079)	0.094 (0.077)	0.095 (0.079)
Risk Attitude	0.627*** (0.213)	0.415** (0.213)	-0.137 (0.233)	0.697*** (0.187)	0.623*** (0.171)
Perception of VTs	0.318 (0.211)	0.225 (0.198)	0.081 (0.205)	0.177 (0.198)	0.065 (0.205)
Spillover Effect	0.270** (0.121)	0.253** (0.123)	0.314** (0.124)	0.290** (0.123)	0.307** (0.124)
Risk Perception	0.072 (0.069)	0.090 (0.069)	0.126 (0.070)	0.095 (0.067)	0.128 (0.070)
Age	-0.011** (0.006)	-0.010 (0.006)	-0.012** (0.006)	-0.011** (0.006)	-0.011** (0.006)
					0.058 (0.189)
Education					
College	0.152 (0.189)	0.167 (0.183)	0.062 (0.188)	0.100 (0.184)	0.058 (0.186)
Post-Graduate	0.458** (0.193)	0.449** (0.184)	0.445** (0.188)	0.373** (0.186)	-0.435** (0.186)
Tree Cover	-3.341 2.384	-1.720 (2.240)	-3.011 (2.402)	-2.654 (2.297)	-3.00e+00 (2.400+00)
Total Land	2.85e-05** (0.135e-05)	3.51e-05** (1.43e-05)	3.175e-05** (1.378e-05)	3.22e-05** (1.41e-05)	3.13e-05** (1.38e-05)
Risk Attitude*Perception of VTs	-0.055 0.058	-0.042 (0.056)	-0.003 (0.057)	-0.029 (0.056)	0.001 (0.056)
Occupation Heterogeneity* Risk Attitude	-0.211* 0.185				
Information Heterogeneity* Risk Attitude		0.059 (0.186)			
Network Efficiency* Risk Attitude			0.789*** (0.253)		
Frequency of Interaction* Risk Attitude				-0.228** (0.096)	
Network Density* Risk Attitude					-0.554** (0.192)
Number of Observations	256	268	251	268	251

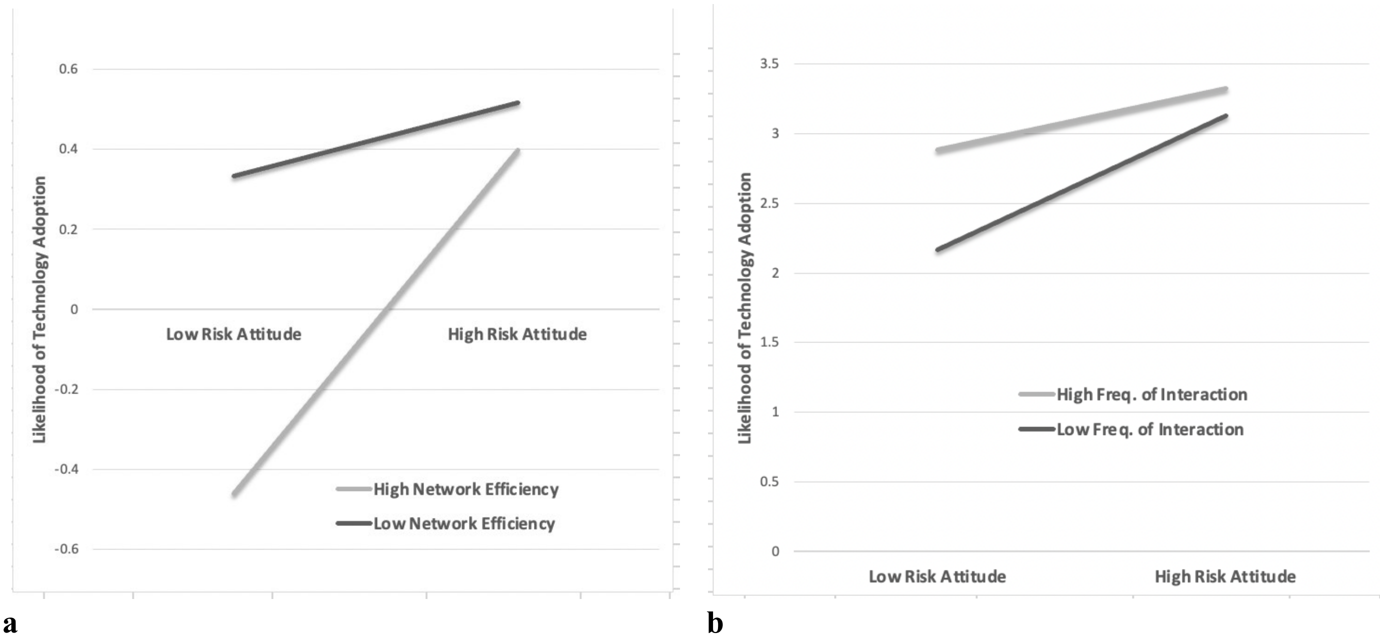

Fig 2. Interaction Plots: a) Interaction between Risk Attitude and Network Efficiency b) Interaction between Risk Attitude and Frequency of Interaction

Conclusion:

Producers need to have access to information regarding new conservation practices and technologies to ensure land management in the face of ecological threats in general and VTs in the context of our study. This study investigates the role of an individual producer's social network on the willingness to seek information about technologies and management practices and the likelihood of new technology adoption with special attention to risk attitudes and producer spillover effects. Our results provide evidence that network composition and information obtained through a producer's social network don't influence an individual's willingness to seek information about new technologies or management practices. However, when it comes to adopting specific technology, like screening and imaging technology, social network measures have a significant impact. Additionally, we found risk attitude and spillover effect positively influence the likelihood of technology adoption. The significant positive impact of the spillover effect confirms that producers are reactive to the effects of VTs that they observe within their neighbor's land and are willing to seek information regarding new practices and technologies and adopt them.

Considering the above results, it is evident that if public and private agencies are interested in addressing negative effects of VTs through changes in producer behaviors, they would be well served to invoke the mechanism of producer personal social networks to ensure effective receipt and dissemination of information regarding the new technology. Such effective information transmission can be combined with existing (and new) environmental policies to address VTs issues in Nebraska (and possibly in other areas where producers have similar profiles).

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