The Role of Social Support on Midwestern Farmers' Willingness to Grow Perennial Bioenergy Crops

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Highlights

- Social support's impact on farmer willingness to grow bioenergy crops are analyzed
- Farmer familiarity with the crops is the most important factor
- Familiarity also mediates the impacts of various influencing factors
- Peer adoption can directly and indirectly affect willingness via its impact on familiarity

Abstract

The lack of farmers' willingness to grow perennial bioenergy crops (PBCs) presents a critical barrier to the emergence of cellulosic biofuel production. The willingness relies on a complex network of economic, environmental, and social drivers, among which the influence of social factors (e.g., the influence of neighborhood, community, and communication) is less understood. This study addresses this knowledge gap via a survey analysis of midwestern farmers. The survey data are analyzed through ordinary least square regression and structural equation model, which together investigate the individual and interactive impacts of multiple factors on farmers' decisions to adopt PBCs. Based on a farm-scale analysis, six statistically significant predictors of farmer willingness to grow PBCs are identified: perception of PBCs' environment benefits, education level, willingness to take risks, familiarity with PBCs, portion of peers already growing PBCs, and support of biorefineries locating in the local community. Among these, the latter three predictors are social support variables. It is found that familiarity with the crops is the most significant predictor of willingness; familiarity is also an important intermediate variable that mediates the influence of many other predictors. In addition, peer adoption can both directly and indirectly affect willingness *via* its influence on familiarity. These findings suggest that it is a pressing need to improve farmers' knowledge of PBCs to promote the adoption of such crops.

Keywords:

Cellulosic bioeconomy; Farm-scale; Social support; Structural equation model; Survey; Willingness.

1. Introduction

Bioenergy is a crucial field that addresses the world's progress toward renewable energy, economic development, and environmental sustainability [1–3]. While existing biofuels are mostly produced from food crops such as corn and soybean using hydrolysis, fermentation, or transesterification, many believe cellulosic biofuels produced from perennial bioenergy crops (PBCs) (such as Miscanthus, *Miscanthus x giganteus*, and switchgrass, *Panicum virgatum*) using biochemical or thermochemical technologies are more promising given the high yield of the PBCs and their various environmental and ecological benefits [4,5]. In addition, PBCs can be grown on marginal lands that are not suitable for food crop production, hence ameliorating the conflict between food and energy for corn-based and soybean-based biofuels [6,7]. Despite the benefits highlighted above, the PBC development in the United States (U.S.) is still limited to small-scale trials mainly for research [8]. As a result, the production of cellulosic biofuel (the primary use of PBCs) in 2020 only met 5.9% of the target of 10.5 billion gallons, the mandate of the Renewable Fuel Standard (RFS) [9]. Therefore, it is of great importance to improve understanding of potential drivers, as well as barriers of PBC adoption, which could be used to design more effective promotion policies for PBCs.

The adoption of PBCs relies on decisions at the farm scale. Economic factors, including the availability of the biomass market, expected return of PBCs, contracts with biorefineries, farmland ownership, etc., are identified as the most important drivers of PBCs adoption [10–14]. Fewell et al. [14] surveyed Kansas farmers for their switchgrass adoption decisions under contract through a choice experiment approach. Their results suggested that uncertainties in PBC production contribute to farmers' lack of willingness to adopt such crops, and the profitability of PBCs must be compatible with other food crops to encourage farmer adoption. Through a similar approach, Khanna et al. [15] found that farmers' willingness to adopt PBCs is negatively correlated with their discount rate and the energy crops' upfront establishment costs, which are the additional crop-specific investment for PBCs. Other non-economic factors, mostly behavior-related factors such as farmer's age, education level, attitude toward the environment, knowledge of PBCs, etc., also play important roles in PBC adoption [11,16–19]. In addition, large-scale adoption of PBCs also requires additional infrastructure for transportation, water, and access to biorefineries [1,20,21].

Despite many studies on PBCs adoption, few investigated the influence of social factors, such as the information and support from their neighbors, local communities, and the society. The factors could be explained as subjective norms following the theory of planned behavior [24], and their impacts have been proven essential for the adoption of novel land use options [22,23]. In general, farmers tend to mimic their neighbors' practices as a result of peer pressure and information diffusion [25–27]; they make land use decisions under specific community and social contexts such as mass media propaganda, access to urban areas, and the proximity of private enterprises and public services [23,28]. Yet, there still needs additional evidences for the social support factor impact as mentioned above, specifically on PBCs adoption. Our study aims to add the evidence by analyzing data from a recent land use survey.

Yang et al. [11] reported a survey on Midwestern farmers' PBC adoption decisions. The survey is designed with a balance of economic, behavioral, and social support factors for land use decisions, including farmers' familiarity with PBCs, their neighbors' land use decisions, and community support. Their analysis revealed that economic factors such as the expected return of PBCs and marginal land availability are the most relevant drivers. The analysis also found social related factors such as information sources and concern on social related barriers for growing PBC as potential indirect predictors. However, as mentioned in Yang et al. [11], such analysis for social factors is exploratory and requires further validation based on more rigorous statistical analyses. Further, the analysis in Yang et al. [11] focused on adoption decisions under choice experiment scenarios, and social factors are not explicitly represented in the scenario design. Thus, it is not clear how social factors may affect farmer willingness to adopt PBCs. Following Yang et al. [11] and using the same survey, the current study specifically addresses the role of social support on the willingness to grow PBCs in general, without the influence of any choice experiment scenario. The collected data are analyzed with ordinary least square regression to investigate how PBC adoption decisions are influenced by those economic, behavioral, and social support factors. Following that, this study further applies a structural equation model to investigate how those factors interactively influence PBCs adoption willingness via a hierarchical structure. Findings from this study would be beneficial for the understanding and promotion of PBC adoption at the farm scale.

2. Survey and data preprocessing

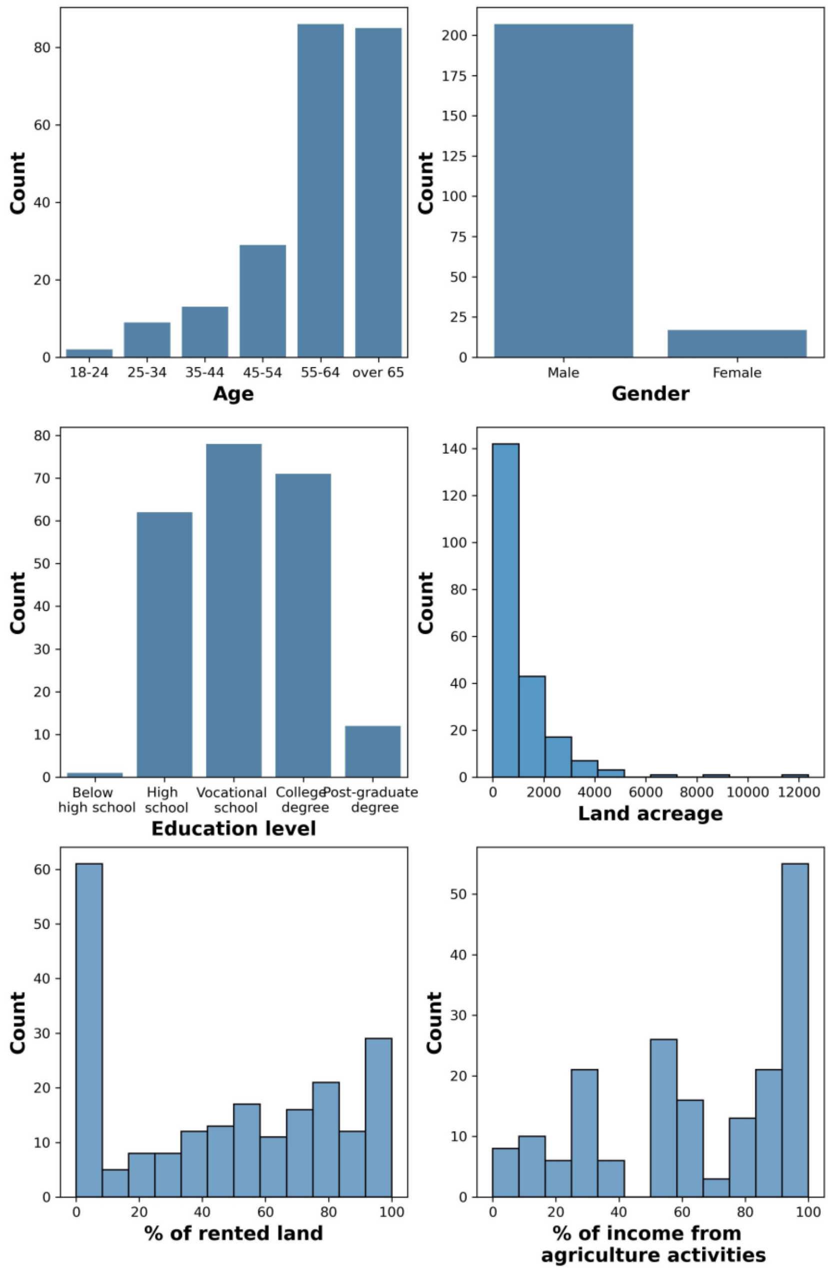

Figure 1. Histograms of respondents' socio-economic variables.

The survey, conducted in late 2019 and early 2020, was sent to 2,500 Midwestern farmers identified from the Farm Market ID database [29]. To ensure an appropriate coverage of farmers with small and large farm sizes, the 2,500 farmers were sampled from the Farm Market ID database using a stratified random sampling technique [30] based on farm size. We collected 242 survey responses from the 2,500 farmers, resulting in a response rate of 9.7%. 17 of the 242 responses contain missing values and were excluded in the analysis of Yang et al. [11]. This study fills the missing values using a KNN model trained with the original sample data and thus uses the full set of 242 samples for the analysis.

Figure 1 shows histograms respondents' socio-economic variables. The respondents are mostly male, aged farmers (85.5% male and 70.7% over 55), and most of them have a high school/vocational school/college degree. Over 75% of respondents work on farms which are smaller than 2000 acres, and very few on large farms over 10,000 acres. About 60% of the respondents own all the farmland they operate; about 19% of them depend heavily on rented land (with >80% of their land rented). About 68% of the respondents have over 50% of their income from agricultural activities, while the rest are less dependent on agricultural incomes.

The survey covers questions on farmers' willingness to adopt three PBCs – Miscanthus, switchgrass, and energy sorghum – in five priority levels from "most unwilling" to "most willing." It should be noted that the willingness defined with our survey questionnaire is different from the adoption decision preference as defined in Yang et al. [11]. Instead, it can be understood as a proxy of inclination or likelihood to adopt PBCs. We designed three sets of companion questions for a comprehensive analysis considering multiple factors: i) economics related (e.g., farm size and participation in crop insurance programs), ii) behavior related (e.g., age and education level), and iii) social support related (e.g., neighbors' land use decisions and participation in government conservation practices). A farmer's willingness to adopt the three PBCs is transformed into numeric values ranging from 1 (most unwilling) to 5 (most willing), and these are averaged to calculate the farmer's average willingness to grow PBCs (*Will_ave*). The survey also includes a choice experiment which asked farmers to choose the acreage of land to be converted into PBCs under specific economic scenarios. As discussed in section 1, answers to the choice experiment are not included in the current analysis. Responses to other survey questions are transformed into explanatory variables in Table S1 in the Supporting Information (SI) to model *Will_ave*.

Several variables in Table S1 are composite variables derived from responses to more than one survey question. *Env_Pct* is calculated as a farmer's average agreement with the importance of two objectives in land management: environmental protection and land preservation. *Land_Mang* is calculated as a farmer's average agreement on the importance of two environmental issues on their land management decisions: climate change and fertilizer and pesticide overuse. *High_Profit* is calculated as a farmer's average agreement with two statements that adopting PBCs can: increase revenue and increase profit reliability under poor weather conditions. *Bene_Env* is calculated as farmer's average agreement with three statements relating to the environmental benefits of PBCs: local water quality improvement, soil quality improvement, and national energy security improvement. *Drawback* is calculated as farmer's average agreement with three concerns of growing PBCs: competition with other land uses, lack of market, and lack of transportation infrastructures.

Table S1 includes six sets of social support variables. *Govp* is included with the assumption that farmers who participated in government conservation programs would be more willing to try new conservation practices such as PBCs. *Fam_ave* was usually included in similar innovation land use diffusion studies as an important intermediate variable to explain farmers' adoption decisions [22,31]. An increase in *Fam_ave* can be considered a result of peer communication, community promotion, and public propaganda. These types of neighborhood communication have shown positive impacts in the adoption of certain farming techniques or crops [32]. *Sup_bio* represents the availability of biomass end-users (i.e., biorefinery) for farmers and is expected to have a positive impact on PBCs adoption. *Com_sup* represents the community's support for growing PBCs in the community, which could be considered as a part of social judgement of PBCs adoption. *Peer* can have multiple impacts on PBCs adoption: i) the increase in peers adopting PBCs would increase a farmer's exposure to information and knowledge of PBCs; ii) as PBCs become more popular, there is peer pressure for farmers to adopt this environmentally friendly land use. Finally, *Info_use* could be used to investigate if farmers' adoption of PBCs could be affected by any source of information they receive.

3. Methods

As the target variable *Will_ave* (farmers' average willingness to adopt PBCs) is a continuous ranging from 1 to 5, we can use a mix of empirical regression models, namely Ordinary Least Square regression (OLS) and Structural Equation Model (SEM), to investigate the predictors of the variable, as the two models are widely used for treating continuous variables. Through a preliminary analysis (Figure S2 of the SI), farmers' familiarity with PBCs (*Fam_ave*) appears to be the most important predictor of *Will_ave*. We use OLS to identify the key drivers for willingness and familiarity, respectively. We then combine the two OLS models into one SEM to show how various factors directly influence adoption willingness or indirectly affect the target variable via the influence of familiarity (here referred to as the mediation effect). In practice, the causal-relationships of *Will_ave* and its influencing factors may show a hierarchical structure [11], but here we limit the mediation variable in the SEM to be only *Fam_ave*, given the SEM complexity constraint posed by the data sample size (242). As a complement to the main SEM, for other important predictors of *Will_ave*, we develop separate OLS models to identify their driving factors and compare the results crossing the multiple OLS models, especially on the key predictors in the OLS models.

During the analysis, a special focus is given to the variables in the social support category. The hypothesis is that social support variables such as *Fam_ave* and community support (*Com_sup*) are key parts in the model of PBC adoption willingness.

3.1 Ordinary Least Square Regression

The OLS model calculates a farmer *i*'s willingness to adopt PBCs as:

$$Will\_ave_i = X_i^T \beta + \varepsilon_i \quad (1)$$

where β is a vector of regression coefficients, X refers to the explanatory variables, and ε is the error term. While the variables in Table 1 could all potentially affect farmers' willingness to adopt PBCs, we add two constraints on the predictors of the willingness OLS model to make the model concise: i) the correlation coefficient between the predictor and *Will_ave* should be larger than 0.03 to make sure the predictor is influential

[33,34], and ii) the correlation coefficient between two predictors should be less than 0.3 to avoid collinearity [35].

Several key predictors (*Risk*, *Fam_ave*, and *Peer*) show clear linear relationships with *Will_ave* (Figures S1-S3 in the SI), which supports the choice of the OLS model. Among them, *Fam_ave* appears to be the most important predictor of *Will_ave* (given its correlation coefficient with *Will_ave* equals 0.282). In fact, familiarity has been identified as an important intermediate variable that mediates the influence of many other more fundamental drivers of willingness in similar land use studies [22,31]. Hence, we build a separate OLS model for familiarity (*Fam_ave*) to identify the drivers that could indirectly influence farmers' willingness to adopt PBCs through the mediation of *Fam_ave*.

3.2 Structural Equation Model

To further reveal how multiple drivers directly influence farmer willingness to adopt PBCs and indirectly influence willingness through the mediation of farmer familiarity with these crops, we use a structural equation model (SEM) to link the two OLS models through the familiarity variable *Fam_ave*.

SEM is a multivariate statistical analysis tool for analyzing structural relationships [36–38]. SEM combines factor analysis and multiple regression analysis to analyze the direct and indirect relationships in a causal-relationship structure that involve one or more latent variables [37]. Given its advantage in analyzing complex multiple variable models and revealing relationships in hidden structures, SEM has been widely applied in social science studies [39–41].

4. Results

4.1 The Willingness OLS Model

The results of the OLS model for farmer willingness to adopt PBCs (hereafter referred to as the willingness OLS model) are shown in Table 1. The modeling results show a good agreement with the farmer responses, where about 84.8% of the variation in farmers' average willingness to grow the three surveyed PBCs could be explained by the model (with an adjusted R^2 value of 0.85). The model also has an F-statistic of 114.3 and a p-value < 0.0001, which all suggest that the model contains helpful information for predicting the target variable *Will_ave*.

Table 1. Coefficients of the OLS model for farmer willingness to adopt PBCs.

	ESTIMATE OF COEFFICIENTS	T-VALUE	P-VALUE
Old	0.198	0.409	0.683
Male	0.128	0.270	0.788
Edu	-0.040	-0.539	0.590
IL	0.120	0.812	0.418
Govp	-0.138	-0.630	0.529
Crop_ins	-0.026	-0.131	0.896
Risk	**0.152****	2.042	0.042
Fam_ave	**0.405*****	4.146	1E-04
Sup_bio	**0.117***	1.915	0.057
Peer	**0.177***	1.94	0.054
Multiple R^2	0.855	Adjusted R^2	0.848
F-Statistic	114.3	P-value of F-stat	2.20E-16

Note: $^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$; coefficients in bold are statistically significant.

Altogether, ten variables are selected as the predictors for the willingness OLS model, among which three are economics variables (*IL*, *Risk* and *Crop_Ins*), three are behavior variables (*Old*, *Male*, and *Edu*), and four are social support variables (*Govp*, *Fam_ave*, *Sup_Bio*, and *Peer*) (Table 1). Four of the predictors show statistical significance, and three of them are in the social support category. Among them, farmer's familiarity with PBCs (*Fam_ave*) turns out to be the most important predictor of adoption willingness with a *p*-value < 0.0001. With one unit increase in farmers' familiarity with PBCs, the average willingness to grow PBCs will increase by approximately 8.9% (Table 1). The impact of *Fam_ave* shows that farmers' willingness to adopt a novel land use option highly depends on their familiarity with the option; this phenomenon is consistent with what was found by Ariti et al. [31] and Lee et al. [22].

4.2 The Familiarity OLS Model

The willingness OLS model shows how various factors affect farmers' willingness to adopt PBCs, among which farmers' familiarity with the crops is most influential. In the following, we further explore potential predictors of familiarity via the familiarity OLS model. Results from the familiarity OLS model provide hints on the potential factors that could indirectly influence willingness via their impacts on familiarity. As shown in Table 2, the familiarity OLS model also shows a good agreement with the farmer responses, where about 95.7% of the variation in farmers' average familiarity to the three surveyed PBCs could be explained by the model (adjusted R^2 value equals 0.957). The model has an F-statistic of 527.9 and a p-value < 0.0001, which suggests a stronger regression performance than the willingness OLS model.

Table 2. Coefficients of the OLS model for farmer familiarity to PBCs.

	ESTIMATE OF COEFFICIENTS	T-VALUE	P-VALUE
Env_pct	0.007	0.155	0.877
Land_mang	0.027	0.463	0.644
Peer	**0.310*****	5.042	1.74E-07
High_profit	**0.359*****	4.120	5.41E-05
Bene_env	**0.482*****	6.331	1.4E-09
Drawback	0.101	1.283	0.201
Knowledge	-0.057	-1.020	0.309
Edu	-0.076	-1.484	0.139
Multiple R^2	0.9567	Adjusted R^2	0.9549
F-Statistic	527.9	P-value of F-stat	<2.20E-16

Note: $^{***}P$<0.01, $^{**}P$<0.05, $^{*}P$<0.1; coefficients in bold are statistically significant.

Altogether eight variables are selected as the predictors for the familiarity OLS model, among which one is an economic variable (*High_Profit*), six are behavior variables (*Env_Pct*, *Land_Mang*, *Bene_Env*, *Drawback*, *Knowledge*, and *Edu*), and one is social support variable (*Peer*). Three of the predictors show statistical significance, and one of them (*Peer*) is in the social factor category. Among the statistically significant variables, *Peer* appears in both the willingness OLS model and the familiarity OLS model, suggesting that it may influence willingness directly or indirectly via the influence of *Fam_ave*. *High_profit* and *Bene_env* only appear in the familiarity OLS model, suggesting their impact on farmer willingness may be indirect via the mediation of *Fam_ave*. It should be noted that the potential indirect influences of *Peer*, *High_profit*, and *Bene_env,* as identified in Table 2, are based on theoretical reasoning, which requires further validation, as detailed the following SEM model in section 4.3.

4.3 The Structural Equation Model

To further validate the direct and indirect influences of the factors identified in sections 4.1-4.2, a structural equation model (SEM) is constructed, using the same factors defined in sections 4.1-4.2. The SEM assumes a hierarchical structure where the impacts of various indirect influencing factors are realized via the mediation of *Fam_ave*. More specifically, it is assumed that *Fam_ave* directly influences willingness, while other factors either directly influence willingness or indirectly influence willingness via their influence on *Fam_ave*.

Table 3. Statistical report of the structural equation model.

Model Statistic	Value	**Criteria**	**Source**
Comparative Fit Index (CFI)	0.884	> .95	[42,43]
Tucker-Lewis Index (TLI)	0.723	> .95	[43]
Root Mean Square Error of Approximation (RMSEA)	0.045	< .06	[43]
Root Mean Square Residual (SRMR)	0.022	< .08	[42]

A critical step in the SEM development is the fitness test. Since relying on one fitness index might lead to inappropriate model design, many suggest that a combination of fitness indices should be used for evaluating SEM models [42,44]. In this study, the model fitness is evaluated via four widely adopted indices [42]: the root mean square error of approximation (RMSEA), the root mean square residual (SRMR), the comparative fit index (CFI), and the Tucker-Lewis index (TLI). The former two indices belong to absolute fit indices for SEMs, which assess how well an a priori SEM model reproduces the sample data. The latter two are incremental fit indices, which measure the proportionate improvement in fit by comparing a target model with a baseline model assuming uncorrelated observed variables. A good performing model should have high CFI and TLI values, and low RMSEA and SRMR values. The recommended ranges of good performance are listed in Table 3. The CFI of our SEM is close to 0.9 (though not over 0.95), and the TLI is also relatively high. The RMSEA and SRMR are smaller than 0.05, indicating that the model's fitting performance is ideal. Considering the relatively small sample size of the survey data, it is reasonable to conclude that the performance of the SEM is statistically valid.

Table 4. Coefficients of the SEM for farmer familiarity to PBCs.

	ESTIMATE OF COEFFICIENTS	STANDARD DEVIATION	Z-VALUE	P-VALUE
Env_pct	0.019	0.045	0.432	0.666
Land_mang	0.000[a]	0.056	-0.009	0.993
Peer	**0.271*****	0.056	4.866	0.000[a]
High_profit	0.100	0.111	0.904	0.366
Bene_env	**0.257*****	0.097	2.665	0.008
Drawback	0.005	0.080	0.060	0.952
Knowledge	-0.058	0.054	-1.086	0.278
Edu	**-0.109*****	0.050	-2.177	0.029

Note: $^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$; coefficients in bold are statistically significant.

[a]the p-value is small and is rounded to 0.000 for consistency.

Tables 4 and 5 show the coefficients of the final SEM model. To avoid correlation among independent variables, age and sex are excluded from the main models. A comparison between the SEM and the two OLS models suggests no significant difference between the statistically significant variables. In the SEM model, *Peer* and *Bene_env* remain influential to familiarity, and the four most important predictors of willingness remain to be *Fam_ave*, *Sup_bio*, *Peer*, and *Risk*.

A visualization of the SEM (Figure 2) shows the central role of familiarity (*Fam_ave*) in predicting willingness (*Will_ave*). *Fam_ave* has the largest coefficient value in the

SEM (which indicates the most important influence), and it mediates the indirect influence of many variables (*Bene_env*, *Edu*, and *Peer*) on *Will_ave*. Meanwhile, economic variables (*Risk*) directly influence willingness without mediation, and behavior variables (*Bene_env* and *Edu*) only indirectly influence willingness via the mediation of familiarity. Among the social support variables, *Peer* both directly and indirectly influences willingness; *Sup_bio* has only a direct impact. Clearly, peer information (*Peer*) appears to be another key predictor of willingness, a conclusion supported by a variety of agricultural land use publications [11,22].

Table 5. Coefficients of the SEM for farmer willingness to adopt PBCs.

	ESTIMATE OF COEFFICIENTS	STANDARD DEVIATION	Z-VALUE	P-VALUE
Edu	-0.044	0.077	-0.568	0.570
IL	0.109	0.142	0.769	0.442
Govp	-0.145	0.213	-0.678	0.497
Crop_ins	-0.008	0.189	-0.042	0.967
Risk	**0.148****	0.076	1.941	0.052
Fam_ave	**0.389*****	0.101	3.870	0.000[a]
Sup_bio	**0.122*****	0.060	2.050	0.040
Peer	**0.178*****	0.089	1.997	0.046

Note: $^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$; coefficients in bold are statistically significant.

[a]the p-value is small and is rounded to 0.000 for consistency.

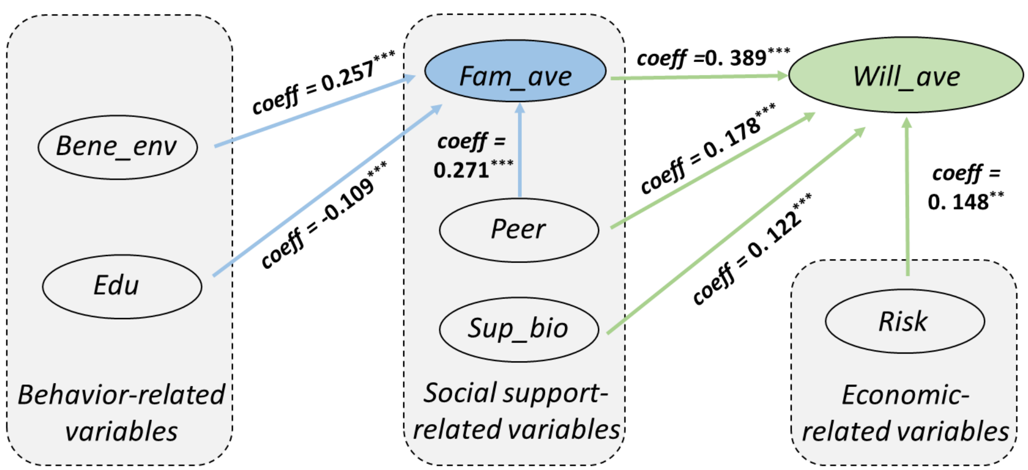

Figure 2. Visualization of the SEM; only statistically significant variables are shown in the figure ($^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$).

5. Discussion

5.1 Impacts of social support variables

Among the six statistically significant predictors of farmer willingness to grow PBCs (*Will_ave*), three of them (farmer familiarity with the crops, *Fam_ave*; portion of peers already adopting the crops, *Peer*; and farmer support for biorefineries locating in his/her community, *Sup_bio*) are social support variables; familiarity appears to be the most important one. The results clearly demonstrate the importance of social support in farmer decision-making regarding PBCs.

The SEM model in Figure 2 suggests an interesting result that the factors affecting farmer willingness to grow PBCs may be indirect via the mediation of familiarity. The model structure follows an intuitive belief that farmers can only be willing to grow PBCs after they have enough knowledge about the crops. In a relevant study about PBCs, Signorini et al. [45] argued that "as agricultural producer learns more about switchgrass and its conveniences, they are likely to understand that the crop itself carries multiple attributes they show a preference for." Similar results are also drawn from Fewell et al. [14] and Skevas et al. [46]. Building upon the findings of the studies listed above, this study further demonstrates the intermediate role of familiarity in mediating the impacts of some factors that indirectly affect willingness. Our conclusion is echoed in a study that investigated the adoption of another novel land use option. Lee et al. [22] used a causal mediation analysis and identified a similar hierarchical structure that the awareness of cover crop options mediates the influence of multiple background characteristics on farmer willingness to adopt such crops in Iowa. Our results, together with those of Lee et al. [22], suggest the central role of familiarity in promoting novel land use options, as discussed in section 4.3.

The model structure in Figure 2 also partially reflects the conclusions in our previous study, which estimates the causal relationship structure of farmers' PBC adoption decisions via Bayesian network analysis in a choice experiment [11]. In that study, familiarity was identified as one of the most influential variables in the adoption decision, and it mediates the impact of peer adoption, which has been identified in Figure 2. Familiarity mediates the impacts of two other variables shown in Figure 2, *Edu* and

Bene_env, while such relationships are not identified in Yang et al. [11]. The causal relationship structure in Yang et al. [11] was identified based on both optimal search and manual adjustment, while the model structure in Figure 2 is believed to be more appropriate given the statistical rigor of the SEM. Figure 2 suggests that behavior factors such as *Edu* and *Bene_env* affect farmer willingness to grow PBCs but only via their influence on farmer's familiarity with the crops. Among them, the impact of *Bene_env* is positive, suggesting that a farmer's awareness of PBCs' environmental benefits is an important part of their knowledge on the crops. Unexpectedly, the impact of education is negative, while most previous studies found education level positively affects willingness and/or familiarity [19,47]. Possible explanation may be related to observed naivety with less educated/informed farmers [48]. The naivety can drive the farmers to believe they know enough about PBCs. The result thus suggests a necessity to provide a more objective measure of familiarity, possibly via a set of quizzes about PBCs to survey respondents. Meanwhile, the result implies that more outreach programs on PBCs are needed to improve farmers' knowledge about such crops.

Peer adoption (*Peer*) is another important variable as it affects both familiarity and willingness. Yang et al. [11] also identified peer adoption as an important factor in farmer adoption willingness, but its impact is only indirect via the mediation of familiarity. Results regarding the impact of *Peer* in both studies reflect the spatial spillover effect of PBCs adoption willingness, as identified by Skevas et al. [47], Swinton et al. [49], and Jiang et al. [19], who suggested that peer communication and peer pressure regarding PBCs could be the major driver. However, the direct impact of *Peer* on willingness identified in Figure 2 demonstrates that noticing the adoption of neighbors can already increase a farmer's willingness to adopt PBCs, even if they still know little about such crops. Therefore, the impact from early adopters in a community may be quicker and stronger than expected, as the farmers in the neighborhood may decide to grow PBCs before they have the same level of knowledge and/or experiences as the early adopters have. It should be noted that the inclusion of *Peer* in the regression models may raise concern regarding the issue of endogeneity; that is to say, the error term might be correlated with the predictor (*Peer*) if the predictor is affected by the regressing target (*Will_ave*) [50,51]. However, our model may not be subject to the endogeneity issue, because the respondents in the survey do not know each other and their adoption would not affect the peer adoption ratio of other respondents. Meanwhile, our survey reflects the value of *Peer* and *Will_ave* at only one specific point of time, and *Will_ave* would only affect *Peer* at future time points.

Farmers' support for biorefineries located in their community (*Sup_bio*) is another key behavior factor identified in Figure 2. A high value of *Sub_bio* provides a sign that farmers are considering future markets of PBCs, which further indicates a higher possibility that they are willing to adopt such crops. A similar result was also identified in previous studies. For example, Embaye et al. [52] noted that the availability of nearby crushing facilities is important for PBCs adoption because well-developed nearby facilities could potentially contribute to a better market for the crops.

Two behavior variables (i.e., perception of the environmental benefits of PBCs, *Bene_env*; education level, *Edu*) in Figure 2 indirectly influence the adoption of PBCs and the impact of one economic variable (willingness to take risk, *Risk*) in Figure 2 is direct. The impacts of the three variables are consistent with the finding of other studies [11,45], except for the impact of *Edu*. As explained above, the negative impact of *Edu* may be related to the observation that less educated/informed farmers may falsely believe they know enough about PBCs [48], and/or they can be convinced with simple or quick knowledge (e.g., following neighbors as discussed above) without deep thoughts or concerns. The two behavior variables are closely connected to the social support factors although they are not included in the social support category of this study. This relates to the mechanism that impacts of behavior factors are realized. As shown in Lee et al. [22] and Wang et al. [53], behavior factors such as education level, age, and gender can have impacts on farmers' land use decisions, but only via the mediation of intermediate variables (many of which relate to the social support variables) such as awareness, social status, and economic capability.

5.2 Limitations

In addition to familiarity (*Fam_ave*), farmer's support for biorefineries (*Sup_bio*) and farmers' willingness to take risks (*Risk*) appear to be statistically significant predictors of their willingness to adopt PBCs (*Will_ave*) in the OLS and SEM models (Tables 1 and 5), and they may also mediate the impacts of other indirect variables. However, the developed SEM in Section 4.3 only explores the factors that can indirectly influence the willingness due to the mediation of familiarity, given the relatively small sample size (242).

Meanwhile, additional survey samples would be needed to verify the difference in model structures identified in Figure 2 and in Yang et al. [11]. We suggest that future research should include more survey samples to further verify the assumptions developed in this study. In addition, a multi-year survey effort would further improve the validity of the model developed in this study, as well as identifying potential changes in behavior resulting from market or policy changes [1,60,61].

5.3 Implications

Dedicated bioenergy crops such as PBCs growing on marginal lands are believed to be a possible solution of the grand global challenge of food, energy, and sustainability [3]. While the first generation biofuel produced from food crops (e.g., corn and soybean) faces the ‘food versus fuel’ dilemma, such conflicts can be alleviated for advanced biofuels produced from PBCs as such crops can be mostly produced on marginal lands (which amounts to over 55.1 million hectares in the U.S. [7]). Meanwhile, PBCs bring multiple environmental benefits including but not limited to erosion prevention, soil nutrient recycling, soil fertility improvement, and pollination; furthermore, it is believed that these environmental benefits can improve the crop production on surrounding agriculture lands [62]. Further, it is believed that PBCs will mitigate carbon emissions from soil [63]. As the entire world is cooperatively trying to achieve the objective of carbon neutralization by 2050 [64], this study could contribute to a more targeted design of promotion policies for bioenergy crop expansion and bioenergy development while supporting other carbon emission reduction measures. Some implications for PBCs policy design are discussed below.

The SEM result in Figure 2 suggests the important role of social support in promoting PBCs. In particular, the peer adoption ratio could directly increase farmer willingness to grow PBCs, and it could indirectly increase willingness by increasing farmer familiarity with the crops. Therefore, a potential policy to promote PBCs could be pilot projects that (financially) support farmers to demonstrate the environmental and economic advantages of PBCs. As simulated in Yang et al. [61] via an agent-based model, it is hypothesized that a successful pilot project would encourage early adoption among an agricultural community, which could further increase farmers' knowledge about the crops and their willingness to adopt. Alternatively, pilot projects for bioenergy and bioproduct facilities, e.g., cellulosic biorefineries or small-scale bio-facilities, could foster an early market for biomass and hence encourage early adoptions of PBCs. Such a strategy echoes a stakeholder's suggestion to "get the supply chain rolling" in a Midwestern bioeconomy stakeholder focus group discussion [61]. The core idea of the stakeholder's suggestion is to establish an early market for the bioeconomy supply chain (including biomass producers such as farmers), and the supply chain would mature as participants learn during the processes [61]. The establishment of pilot projects for bioenergy and bioproduct facilities would also affect farmer willingness to adopt PBCs via the influence of *Sup_bio*, if the pilot project could provide a good price for biomass and win the support from local farmers.

Another potential means to improve PBCs adoption is to increase farmers' familiarity with the crops. As validated by multiple past researchers [65–67], advertising and outreach programs focusing on the characteristics, economic, and environmental payoffs of PBCs are prioritized in promotion campaigns. Potential beneficial courses of action are related to another variable *Bene_env*, which looks at whether the farmers are aware of the environmental benefits of growing PBCs. In other words, and as also mentioned by past research [14,68,69], the current mission is to alert farmers of the unique characteristics of PBCs. Some of those characteristics are especially preferred by them, including their potential contribution to the environment and other benefits of the nation.

Alternatively, policymakers targeting PBCs promotion could focus on the variable *Risk*. If farmers can manage their risk and be 20% less risk-averse, they tend to be ~15% more willing to grow PBCs on average (Figure 2). Therefore, policymakers could manage to reduce the risk that are involved in economic loss, climate threats, and lack of local market [1,14]. Agricultural subsidies and government insurance projects could also be potential actions to take [70–72].

6. Conclusion

This study investigates the knowledge gap in the impacts of social factors (e.g., neighborhood knowledge, community communication, and shared practices) on farmers' willingness to grow PBCs. As revealed through a survey analysis of midwestern farmers and a structural model that together investigate the economic, behavioral, and social drivers on farmer decision-making, this study highlights the importance of social variables, such as familiarity with PBCs (*Fam_ave*), peer adoption ratio (*Peer*), and support of biorefineries (*Sup_bio*) on farmer willingness to grow PBCs. Combining two Ordinary Least Square (OLS) regression models that address farmers' familiarity and willingness with PBCs, a Structural Equation Model (SEM) provides insight into the variables' direct and indirect drivers. From both OLS models, six statistically significant predictors of farmer willingness to grow PBCs are identified (farmer agreement with the environmental benefits of PBCs, *Bene_env*; education level, *Edu*; farmer's average familiarity of PBCs, *Farm_ave*; portion of peers already adopting PBCs, *Peer*; support of biorefinery building in the local community, *Sup_bio*; and willingness to take risks, *Risk*), and three of them (*Fam_ave, Peer, and Sup_bio*) are social support variables. Overall, *Fam_ave* appears to be the most significant predictor of farmer willingness to adopt PBCs, and the impacts of many other predictors are only realized via their influence on *Fam_ave*. Other variables such as *Peer* affect both familiarity and willingness. Our findings suggest the potential for improving PBCs policies through social programs such as pilot projects for farmers and bioenergy facilities. The pilot projects could establish an early market for PBCs, which could further attract early adopters of PBCs and increase other farmers' willingness of adoption via the influence of *Peer* and *Fam_ave*. Meanwhile, the cellulosic bioeconomy could be further enhanced by increasing farmers' familiarity with PBCs and minimizing farmers' risk perceptions.

Supporting Information

Supporting information include three tables (Tables S1-S3) and three figures (Figures S1-S3).

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Figure Captions

Figure 1. Histograms of respondents’ socio-economic variables.

Figure 2. Visualization of the SEM; only statistically significant variables are shown in the figure (***P<0.01, **P<0.05, *P<0.1).