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The Role of the Social Network in Adopting New Turfgrass Varieties: An Analysis of Twitter Data

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Abstract. **This study examines the effect of social learning on new turfgrass variety adoption decisions using data from 231 turfgrass professionals' Twitter accounts between 1 Jun 2018 and 31 Dec 2019. To determine the social learning effect, we decompose networking effects into social learning, individual-level and group-level similarities, herd behavior, and clustering effects. Our study estimates a spatial autoregressive probit model that directly incorporates the social network structure to account for unobservable networking effects and potential reflection problem. A Bayesian estimation procedure is used to alleviate the convergence problem caused by the complexity of model specification. Empirical results show that the social learning effect positively influences the new technology adoption and was greater than herd behavior effect. The results also suggest that turf professionals rely more on suggestions and information from online social networking among themselves than recommendations from advisors.**

Factors affecting new turfgrass variety adoption have been a key interest of many stakeholders such as breeders, producers, and marketers in the horticultural production system because adopting new technology significantly affects the environment, welfare, and sustainability of horticultural industries (Beaman et al. 2021; Yue et al. 2021). New technology development, such as developing a new turf variety with better shade tolerance, is a long-term project that requires many inputs, and its return largely depends on consumer adoption of the newly developed technology (Ghimire et al. 2019). Technology adoption is often unpredictable, thereby causing significant uncertainties that hinder development and investment in the next phase (Bhaskaran and Krishnan 2009). Earlier studies of social network analyses indicated that consumers' networking behavior via social media has become an important factor for new technology adoption decisions in the horticultural and agricultural sectors because information exchange through the internet has emerged as a key communication and networking tool (Miller and Mobarak 2015; Mills et al. 2019; Philocles et al. 2023).

However, not all networking channels deliver valuable information or induce turf professionals' adoption of new technology because networking characteristics, such as the purpose of networking, govern the quality of information and corresponding decision-making process through the network (Beck et al. 2014). Without appropriate information exchange through networking, the technology diffusion process could be slow and unsustainable or even result in a negative cycle of nonadoption (Munshi 2004; Straub 2009). Thus, identifying the effect of networking to seek and learn more information, i.e., the information-intensive networking effect, should be an important task involved in the sustainable new technology adoption process in horticulture.

Sorting the information-intensive networking effect from the overall social networking effect can be challenging. As Manski (1993, 2000) pointed out, the social networking effect is difficult to identify when there is insufficient information regarding the social networking process. Accordingly, without accounting for unobservable information, it would be difficult to distinguish intensive social networking (learning effect) from other effects, such as those related to the individual's mimicking behavior (i.e., the reflection problem) (Hsieh and Lee 2016; Liu et al. 2014; Manski 1993).

Previous studies have attempted to address the reflection problem in several ways. For instance, Johnsson and Moon (2021) suggested that unobserved information of networking processes could be accounted for via a two-stage estimation method; however, this approach assumes that the unobservable information is only oriented in individual-level characteristics such as demographics. Besides, this individual-level-only approach may neglect other networking effects such as group-level effects and network structure effects (Lobel and Sadler 2016; Santos and Barrett 2008). Not accounting for group-level and network structure effects could be problematic because they may significantly differ from individual-level effects in terms of the networking process. Each individual in the network may choose who to communicate with based on their interests and preferences (individual-level). However, some individuals prefer networking with someone in the same profession because they tend to share similar standards and are relatively easy to communicate with (group-level) (Huber and Steinmayr 2021). Furthermore, some individuals could obtain information indirectly from a peer of one of their own peers, and the probability and frequency of this indirect interaction are based on the individual's social position (popularity) in the network (network structure) (Liu et al. 2014). Therefore, biased inferences on networking effects may occur if group-level and network structures are not accounted for. Moreover, the approaches that overlook group-level and network structure aspects to the reflection problem could be more problematic in online networks because social media is less constrained and more heterogeneous than in-person networks (Li 2011).

The objective of this study is to estimate the social learning effect, represented by information-intensive networking, on new technology adoption using Twitter data. To identify the learning effect from confounding social networking effects, we decomposed social networking effects into the following four categories: social learning, group-level and individual-level similarities, herd behavior, and clustering effects. We consider information-intensive networking the most potent social signal of the online network platform (e.g., the retweet action on Twitter) (Mills et al. 2019; Rath et al. 2017) and assume non-learning networking effects come from the following: group-level (or institutional)

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similarity (e.g., norms or traditions shared within each profession); individual-level similarity (e.g., caused by an individual's socioeconomic attributes); herd behavior following others' ideas or opinions in the network to which each individual belongs; and clustering behavior caused by social contiguity (Cohen-Cole et al. 2018; Jackson and López-Pintado 2013; Mele 2021; Snijders et al. 2010).

Our results show that the social learning effect positively influences new technology adoption and is greater than the herd behavior effect. The results also suggest that turf professionals rely more on suggestions and information from online social networking among themselves than recommendations from advisors.

Literature Review

Overview of social network analysis studies on new technology adoption. Many studies in the literature about social network analyses have constantly argued that social networking plays an important role in the information flow and adoption of new technologies (Bandiera and Rasul 2006; Conley and Udry 2010; Maertens 2017; Miller and Mobarak 2015). The studies also pointed out the importance of identifying an accurate networking effect by distinguishing the difference between learning (e.g., adoption decisions based on the expected benefits of introducing a new technology) and other effects such as imitation (e.g., adopting a new technology by mimicking the behaviors of others) (Conley and Udry 2010; Maertens and Barrett 2013; Manski 2000). During the technology adoption process, imitation does not guarantee the generation of a rational expectation of new technology adopters; however, it implies inefficient use of new technologies (Manski 2000). Lee et al. (2013) argued that the innovation effect (i.e., adopting a new technology to enjoy its benefit) is more effective for increasing the adoption rate than the imitation effect over time.

Identifying effective networking processes (e.g., information-intensive networking) is critical for sustainable new technology development and adoption processes. Nonetheless, the social networking effect is difficult to identify, particularly because of its complexity; furthermore, social networking between individuals often depends on personal preferences and corresponding attributes, which are hardly observable in data because of practical complications such as privacy issues. The omitted information problem in the analysis of the networking effect would likely lead to biased estimates and, thus, incorrect inferences of the social networking effect on a new technology adoption decision, which is called the reflection problem (Manski 1993, 2000).

Many studies have made various attempts to remedy the reflection problem. A few examples of these efforts include using rich datasets that can allow one to account for most of the networking-related information (Conley and Udry 2010; Maertens 2017), using an experimental design that controls externalities of the networking effect (Santos and Barrett 2008), using proxy variables for personal attributes to account for unobservable private information (Boucher and Fortin 2016), assuming a form of networking-based unobservables (e.g., binary variables), and gauging them through the Bayesian approach (Hsieh and Lee 2016). However, these approaches hinge on the quality of datasets, researcher's choices of proxy variables, and underlying assumptions on social networks. Thus, these approaches may lack external validity because of their subjective frameworks and assumptions and may not provide generalized inferences of networking effects (Boucher and Fortin 2016).

Factors affecting social networking effects. Previous studies suggested various factors that affect the networking process. The group-level difference, such as homophily, is considered one of the most basic and significant factors in social networking effect (Jackson and López-Pintado 2013). Homophily refers to the tendency for people to seek out or be attracted to those who are similar to themselves (Jackson et al. 2017). Following the definition of homophily, McPherson et al. (2001) suggested that one can use socioeconomic variables to control similarities between individuals and groups on social networking and its outcome. Nonetheless, as Bandiera and Rasul (2006) stated, socioeconomic variables alone may not be capable of accounting for all differences in networking. Therefore, controlling only individual-level similarities (e.g., demographics) may result in the omitted variable problem and, consequently, the reflection problem when estimating the networking effect (Bandiera and Rasul 2006; Manski 2000), thus raising the necessity for a systematic investigation of the factors causing differences in the networking process. Katona et al. (2011) and Maiz et al. (2016) reported that individual-level differences in social networking are caused not only by socioeconomic attributes but also by networking behaviors, such as who interacts with whom and for what reason (Conley and Udry 2010). However, this approach raises more complexity in the analysis because potential factors of networking behavior are enormous and difficult to observe. To overcome this complexity, previous studies suggested that one can use network structure measures, which represent the networking characteristic of each individual, as a proxy of this networking behavior (Himelboim et al. 2017; Jackson et al. 2017; Liu et al. 2014; Maiz et al. 2016). However, only a few studies have provided empirical applications of this approach, particularly those related to the new technology adoption process.

Adjacency matrices and network measures. The adjacency matrix represents a networking system that describes social distance or contiguity between individuals (Badinger and Egger 2011; Liu and Lee 2010). Previous studies suggest that directly incorporating networking system in a model could allow one to estimate more accurate networking effects, including direct (e.g., the effect of interactions between my friends and myself) and indirect (e.g., the effect of interactions between my friends and their neighbors on myself) networking processes (Leenders 2002; Pinkse and Slade 2010; Zhang et al. 2013).

A few studies in the sociology literature claimed that network measures, including degree centrality, eigenvector centrality, and clustering coefficient, reflect networking characteristics of each individual (Snijders et al. 2006, 2010). Borgatti and Halgin (2011) and Himelboim et al. (2017) stated that the individual's networking choice is made typically based on unobservable factors such as preference, and that the network structure determines how information flows in the online network. Therefore, incorporating the network measures and adjacency matrix in the regression model would result in better estimates for the social network analysis, particularly for online social networking, by accounting for structure-based networking behaviors at individual and group levels (Cohen-Cole et al. 2018; Lin 2010).

Methodology

This section discusses the procedure of identifying the information-intensive networking effect by filtering out other confounding effects such as individual-level similarity, group-level similarity, herd behavior, and clustering effects (Leenders 2002; Liu and Lee 2010; Lobel and Sadler 2016; Snijders et al. 2010). First, we discussed each of the non-learning networking effects that need be controlled in our econometric model. Then, we described the model specification that includes adjacency matrices, network measures, and other control variables. Finally, we explained in detail how the estimation process works under the Bayesian framework.

Non-learning networking effects. Following earlier studies, individual-level and group-level differences in networking are divided into four main categories, as illustrated in Fig. 1 (Himelboim et al. 2017; Leenders 2002; Snijders et al. 2010). In general, group-level and individual-level similarities could be captured with observational data, and many social network analysis studies in the economics literature attempted to address the similarities using socioeconomic variables (Conley and Udry 2010). However, most herd behavior and clustering effects are not directly observed from socioeconomic data and can be captured only through the network structure (Himelboim et al. 2017). Each effect can be described as follows:

- Group-level similarity (i.e., network fixed effect) is the tendency for individuals in the network to behave similarly under a similar institutional environment. Such institutional similarity may hinder networking from a convergence of consensus (e.g., evaluating the usefulness of new technology) (Golub and Jackson 2012; Manski 1993).

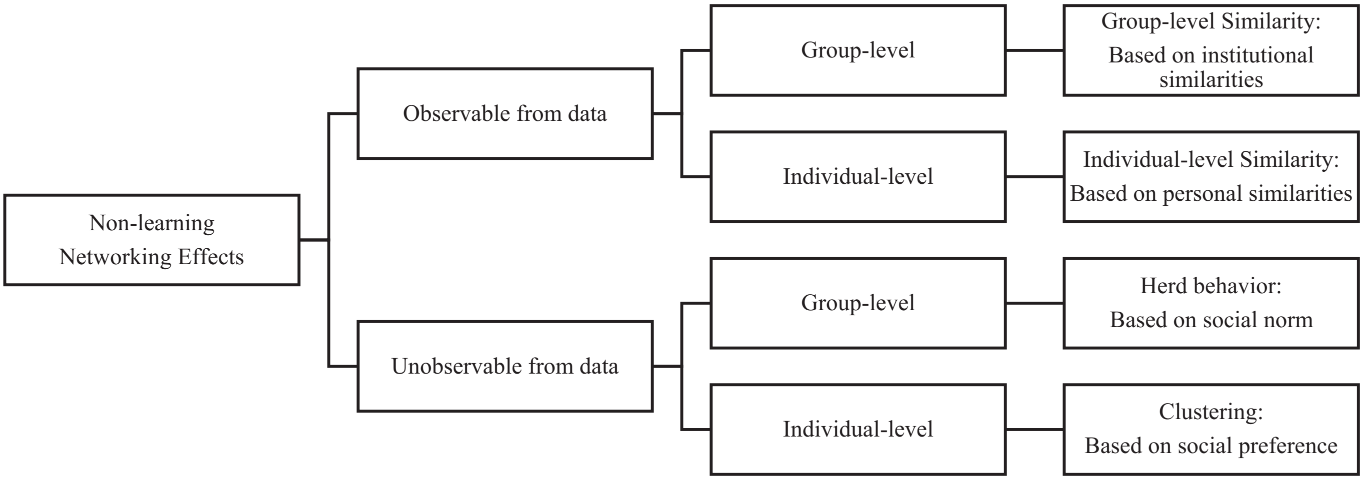

Fig. 1. Non-learning networking effects.

- Individual-level similarities such as the demographic status may cause an imitating effect for people who share the same individual status by homophily (Durrett and Levin 2005). Therefore, group-level similarity and individual-level similarity both may hinder the learning process of information exchange during networking (Golub and Jackson 2012; Santos and Barrett 2008).
- Herd behavior is the tendency of individuals in a network to act collectively toward aggregated opinions such as social norms (Bernheim 1994; Cohen-Cole et al. 2018). When the herd behavior exists in a particular network, individuals tend to regress to their neighbor's aggregated opinion rather than making their own choice through social learning (i.e., mimic the behavior of others) (Bernheim 1994).
- The clustering effect explains people's tendency to be acquainted with friends of friends (Mele 2021). Therefore, when the clustering effect is high, individuals are less likely to communicate with someone outside their social circle, which implies that the clustering tendency could negatively impact the learning process by hindering network expansion (Peng and Mu 2010).

Herd behavior and clustering can be considered similar to similarity measures. However, the underlying logic of herd behavior and clustering differ from similarity. Unlike similarity, herd behavior and clustering represent the tendency to congregate because of individuals' social proximity rather than similarity in affiliated institutions or social status. The three concepts and their effects on social networking are not necessarily aligned (Zhou 2011). Therefore, similarity, herd behavior, and clustering effects need to be controlled differently. Nevertheless, herd behavior and clustering as network heterogeneities have rarely been examined empirically in social network studies, particularly with regard to the individual's decision to adopt technology.

Overall, many previous studies suggested that specifying and controlling both individual-level and group-level heterogeneity are essential to accurately assess the information-intensive networking effect (Hsieh and Lee 2016). Considering both individual-level and group-level effects of networking can provide policy and marketing implications by allowing an understanding of what level of networking is more effective for encouraging technology adoption through online networks. Our study incorporated all four network measures, group-level similarity, individual-level similarity, herd behavior, and clustering, along with adjacency matrices in our econometric model.

Model specification. A Bayesian spatial autoregressive (SAR) probit model was used during our study to estimate the social networking effect on the decision to adopt new technology. The SAR model assumes that variations caused by spatial differences between observations could be explained by a geometric system (i.e., adjacency matrix), not by an unobservable error term, as in a spatial error model (LeSage and Pace 2009). This specification is suitable for the social network analysis because the networking system is similar to a geometric system in that an individual's location and neighborhood determine the individual's influence on others, and because this specification assumes that the networking effect can be explained by estimates rather than something inexplicable (i.e., error term) (Cohen-Cole et al. 2018).

Following the work of LeSage and Pace (2009), Zhang et al. (2013), and Liu et al. (2014), we specified a Bayesian SAR model with two adjacency matrices as follows:

$$Y^* = \rho_1 W_1 Y^* + \rho_2 W_2 Y^* + X\beta + e,$$

$$e \sim N\left(0, \sigma^2 I\right), \qquad [1]$$

where Y^* is a vector ($n \times 1$) of a latent variable that links to the observed binary outcome y_i: if $y_i = 1$, then adopt a new variety (i.e., $y_i^* > 0$); otherwise, $y_i = 0$ (i.e., $y_i^* \leq 0$) for individual i ($i = 1, \ldots, n$). W_1 and W_2 are adjacency matrices ($n \times n$) with zero-diagonal elements of information-intensive and simple networking, respectively. ρ_1 and ρ_2 are networking coefficients corresponding to W_1 and W_2, respectively. X represents the covariate matrix with k variables ($n \times k$), including demographic, profession, and network structure measures. β is a corresponding coefficient vector ($k \times 1$). e is a normal error term vector ($n \times 1$). The term WY^* describes that the adoption decision of individual i is correlated with their position in network W and corresponding social interaction with other decision-makers and their adoption decisions (Cohen-Cole et al. 2018).

Adjacency matrices W_1 and W_2 are based on social interactions between individual i and j ($i \neq j$). Let us consider a simple adjacency matrix W with three individuals as in Fig. 2. In matrix W, if individual i is socially adjacent to individual j, then $w_{i,j} = 1$; otherwise, $w_{i,j} = 0$.

For instance, $w_{12} = 1$ means that individual 1 is socially adjacent to individual 2, whereas $w_{23} = 1$ indicates that individual 2 is adjacent to individual 3. This example shows a social interaction between individuals 1 and 2 and between 2 and 3, but there is no direct interaction between individuals 1 and 3. Nonetheless, an indirect networking effect could exist between individuals 1 and 3 through individual 2 as a waypoint. Therefore, this adjacency matrix system can account for all direct and indirect interactions between individuals in the network (LeSage and Pace 2009).

$$W = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

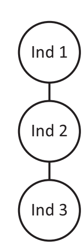

Fig. 2. An example of the adjacency matrix.

Adjacency matrices, W_1 and W_2, are constructed based on participants' "retweet" and "reply" actions to represent their information-intensive and simple networking behaviors, respectively. We consider "retweet" a strong social signal because one would retweet a tweet when one agrees with a tweet or learns from a tweet and even would like to share one's opinion and learning with others (Mills et al. 2019; Rath et al. 2017; Suh et al. 2010). However, "reply" is considered a weak signal because it is an action that one can perform simply to maintain a relationship with no specific reason (O'Dea et al. 2018) or to imitate others' behaviors without actual information exchange (Dutta et al. 2021; Mills et al. 2019). For example, Macskassy and Michelson (2011), Schantl et al. (2013), and Yuan et al. (2016) also agreed that retweet behavior is mainly driven by the content of tweets (i.e., the information contained in tweets) and has a significant explanatory power to predict information diffusion patterns, whereas replying is based on the social factors such as relation between users (rather than the content of the tweet) and has a less significant explanatory power than retweet for predicting an individual's networking behavior. Accordingly, our study considered that W_1 represents individuals' information-intensive networking, i.e., social learning, whereas W_2 represents their imitating behavior (i.e., herd behavior) (Maertens and Barrett 2013; Shen et al. 2016).

Demographic, group, and network structure variables are included in X to control individual-level similarity, group-level similarity, and clustering effects, respectively (Fig. 1). Therefore, after accounting for herd behavior by W_2 along with variables are included in X, we considered that ρ_1, the coefficient of W_1, represents the social learning effect on new technology adoption decisions (Mills et al. 2019; Rath et al. 2017).

Specifically, for each individual i, the vector X_i is formed as follows:

$$X_i = [D_{i1}, D_{i2}, D_{i3}, D_{i4}, White_i, Male_i, Price_i, \\ Clus_i, Deg_i, Cent_i, Cent_i^{adv}], \qquad [2]$$

where dummy variables, D_{ij} and $j = 1 \ldots 4$, represent turfgrass professional groups: if individual i belongs to group j, then $D_{ij} = 1$; otherwise, $D_{ij} = 0$, $White_i$ and $Male_i$ are demographic variables representing the individual's race and gender. If individual i is white, then $White_i = 1$; otherwise, $White_i = 0$. If individual i is male, then $Male_i = 1$; otherwise $Male_i = 0$. $Price_i$, $Clus_i$, Deg_i, $Cent_i$, and $Cent_i^{adv}$ are sod price, clustering coefficient, degree centrality, eigenvector centrality, and networking with advisors, respectively.

The clustering coefficient ($Clus_i$) measures the degree of an individual's clustering behavior with peers. This coefficient has a value between 0 and 1: 0 denotes no peer interaction and 1 denotes all peers are socially adjacent, indicating that the individual is surrounded by people who already know each other (Watts and Strogatz 1998). Degree centrality (Deg_i) indicates each individual i's number of direct connections, which explains each individual's degree of direct influence on networking (Maharani and Gozali 2014; Oldham et al. 2019). However, the eigenvector centrality ($Cent_i$) measures the degree of each individual's level of influence in the overall network, including both direct and indirect (i.e., peers' peer) connections (Wu et al. 2013).

The advisor networking effect variable ($Cent_i^{adv}$) is the centrality measure between individual and advisor groups (Bonacich 1991; Brass et al. 2004). Advisors (e.g., consultant, university faculty, researcher) are not included in our model because they are not decision-makers for new variety adoption. Nonetheless, advisors could transfer information and make recommendations to decision-makers through the networking process and could affect an individual's adoption decision (Wang et al. 2020). Thus, accounting for advisors' influence on the adoption decision is essential to ensure the validity of this model and could also provide meaningful policy implications (Everett and Borgatti 2013).

Following the work of Bonacich (1991), the advisor networking effect on an individual's adoption decision is derived as follows:

$$\lambda \begin{pmatrix} g \\ p \end{pmatrix} = \begin{pmatrix} 0 & A^T \\ A & 0 \end{pmatrix} \begin{pmatrix} g \\ p \end{pmatrix}, \qquad [3]$$

where g is the eigenvector (i.e., centrality score) of each group; p is the eigenvector of each individual; λ is the eigenvalue (scalar); A is a $i \times j$ rectangular matrix that shows the membership of individual i in group j; and A^T denotes the transpose of A. Eq. [3] describes the bilateral relationship between groups and individuals. The eigenvectors g and p explain level of interactions between groups and individuals at group and individual levels, respectively. Here, the centrality measure p is calculated given that each individual is aware of the presence of advisor groups.

In practice, we calculate the eigenvector p via Eq. [3] with the data including advisor groups, and we use the calculated p as a covariate vector as a part of X in Eq. [1]. Therefore, the centrality measure p would represent the degree of each individual's social interaction with advisor groups.

We expect that W_1, W_2, Deg_i, $Cent_i$, $Clus_i$, $White_i$, and $Cent_i^{adv}$ would have positive effects on individuals' adoption decisions, whereas $Price_i$ and $Male_i$ would have negative effects (Wang et al. 2020; Wood et al. 2014). In addition, we expect that W_1 would have a larger impact than W_2 on the adoption decision (Boyd et al. 2010; Mills et al. 2019). Additionally, social networking with advisors ($Cent_i^{adv}$) may show an insignificant effect for some professional groups that value their own experiences or information from peers more than suggestions from advisors (Conley and Udry 2010).

Potential multicollinearity problems between network structure measures, between adjacency matrices, and between adjacency matrices and network structure measures could raise the likelihood of a type II error. However, a preliminary data analysis showed that no variance inflation factor of network structure measures was more than 5 (i.e., no serious multicollinearity between network structure measures), and none of the eigenvalues of the weight matrix in the data-generating process ($I - W_1 - W_2$) were close to 0 (i.e., no serious collinearity between adjacency matrices). We also explored three alternative models to show the potential impact of specifications on parameter estimates, particularly on estimates of professional groups, network measures, W_1, and W_2. The three models are derived from the base model Eq. [2] by imposing the following parameter restrictions: $\beta_{Cent\_adv} = 0$, $\beta_{Deg} = \beta_{Cent} = \beta_{Clus} = 0$, and $\beta_{Deg} = \beta_{Cent} = \beta_{Clus} = \beta_{Cent\_adv} = 0$.

Estimation of the Bayesian SAR probit model. Our Bayesian estimation procedure samples estimates from a posterior distribution of parameters $P(\beta, \rho_1, \rho_1, Y^* | Y)$ given the data Y and prior distributions. We consider that β follows the multivariate normal distribution, and that ρ_1 and ρ_2 follow the four-parameter beta prior (Hanson 1991; LeSage and Pace 2009) as follows:

$$\beta \sim N(c, T), \qquad [4]$$

$$\rho_1 \sim Beta4\left(a, b, \frac{1}{2}\varphi_{1,min}^{-1}, \frac{1}{2}\varphi_{1,max}^{-1}\right),$$

$$\rho_2 \sim Beta4\left(c, d, \frac{1}{2}\varphi_{2,min}^{-1}, \frac{1}{2}\varphi_{2,max}^{-1}\right),$$

where c and T are hyperparameters mean and variance for normal prior, a, b, c, and d, are shape parameters that dictate the shape of distribution (higher share parameters result in smaller variance; therefore, higher share parameters imply more informative prior), and $\frac{1}{2}\varphi_{min}^{-1}$ and $\frac{1}{2}\varphi_{max}^{-1}$ are range parameters, i.e., lower and upper bounds of the corresponding beta distribution, respectively. These prior settings allow the implementation of the parameter space of $\rho_1 + \rho_2$ that ensures convergence (Smith and LeSage 2004). The interdependence between ρ_1 and ρ_2 is imposed via a Gibbs sampling process.

In general, the posterior distribution is unlikely to be obtainable through an analytical approach because of its complexity. Therefore, a practical way of sampling parameters via posterior distribution is to use Gibbs sampling through the Markov Chain Monte Carlo process for conditional density of each parameter distribution (Wilhelm and de Matos 2013). The Gibbs sampling process enables the generation of posterior samples without deriving a high-dimensional joint distribution function of posterior distribution (Geman and Geman 1984; LeSage and Pace 2009).

Data

To estimate the impact of information-intensive networking and social networking with the advisor group on new technology adoption, we collected Twitter account data from 401 individuals (231 turfgrass professionals and 170 advisors), including the tweet history, contents, and tweet interactions (retweets and reply) for the period from 1 Jun

2018 to 31 Dec 2019. The professionals and advisors were selected from the Twitter follower list of a renowned turfgrass breeder to ensure expertise and credibility of the networking process regarding new turfgrass adoption. We expected that social networking of these professionals and advisors mostly focused on warm-season grasses because research interests of the Twitter host and most followers, particularly those who are researchers at various universities, lie primarily in breeding programs for warm-season grasses. The data period included the most recent 6 months before the spread of coronavirus disease 2019 (COVID-19). We tried to avoid the pandemic period because it could significantly affect individuals' social networking as well as new variety adoption behaviors.

The Twitter account data were collected by a data collection company using the Twitter application programming interface, which allowed access to the Twitter database via software such as R or Python. Then, we compiled the data with R and Ucinet for the social network analysis. Turfgrass professionals included managers of sports facilities at campuses of colleges and universities, professional sports (football, baseball, and soccer) field managers, sod producers, golf course superintendents, and public turf managers. The advisor group consisted of turf management suppliers, university faculty and researchers, as well as private researchers and consultants. Our data included a total of 170 advisors and 231 professionals; of these, 156 advisors and 221 professionals were from the United States, whereas the rest were from 14 different countries in Asia, Europe, Africa, and South America.

The original dataset had 1143 Twitter followers; however, we excluded 742 followers who were neither turfgrass professionals nor advisors, had not been active on Twitter, or were not able to be identified by race and gender. We considered 231 turfgrass professionals and 170 advisors as decision-makers and influencers, respectively, for technology adoption. Our econometric model estimated the direct impact of social networking among professionals on technology adoption as well as the indirect impact of advisors on technology adoption via networking with professionals. To capture the indirect impact, a centrality measure between advisors and decision-makers was calculated according to Bonacich (1991).

Network participants' demographic information was first collected from each professional's Twitter profile. Then, a follow-up survey was conducted through the Twitter direct message (DM) to ask additional questions about the adoption of new varieties along with participants' demographic information (gender, race, and education). A copy of the survey questionnaire is included as Fig. 3. The survey commenced on 1 Feb 2022, and it was conducted over the span of 4 weeks. Over that 4-week time period, weekly reminders were sent to participants to ensure their timely responses. The survey was approved for exemption by the institutional review board (protocol number: IRB–21–22). The response rate varied by each question as follows: 19.4% for adoption decisions and related information, such as adopted varieties and applied data; 12.1% for race and gender information; and less than 5% for education level (education level was excluded from the analysis because of the low response rate).

1) By answering "Yes" to this question, you are indicating that you are at least 18 years old, and understood this consent form and agree to participate in this study.

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2) When did you install new turfgrass varieties
between 2018 and 2021?

If you installed more than once, please indicate all month-year of applications.

(If you did not install any new varieties during this period, please go to (3).

3) Please state names of varieties.

4) What is your highest level of education?
(a) Less than 12th grade
(b) High school diploma
(c) Some college
(d) B.S./B.A. or higher graduate

5) What is your race and gender?

6) How long have you been working as a turfgrass professional?

Please choose "Reply" in DM tab and write your answers after indicating question numbers.

For example, you can write:
1) Yes
2) April-2018, August-2018, April-2019
3) Bermudagrass
4) b
5) White-female
6) 20

Thank you for completing the survey.

Fig. 3. Survey questionnaire sent via a Twitter direct message (DM).

We were able to collect 231 professionals' race and gender information from account owners' biographical profiles and the follow-up surveys via Twitter DM. Given that the network participants were mostly professionals, the relevant information was typically disclosed in their bios. The demographic information obtained from individuals' bios was cross-checked with survey responses. We were able to collect 28 additional participants' gender and race information from the DM survey. The survey also asked professionals about turf varieties they had during the study period to find the market price of sod for each grass variety (Miller 2022). If the professional used two or more varieties, then the average price was calculated for sod price.

Our dependent variable, the adoption of a new turfgrass variety by professionals, was determined by using a three-step verification process. First, we extracted the adoption information from professionals' tweets using keywords that implied professionals' decisions to adopt a new turfgrass variety (Zhang et al. 2022). If a tweet contained the following keywords, then we considered the tweet a signal of adoption decision: "turfgrass" and "adoption" (or "adopt"); "turfgrass" and "installation" (or "install"); or "Latitude 36" or "NorthBridge" or "TifTuf Bermuda". The keyword search was executed using R packages *quanteda* and *dplyr*. Second, among all tweets of professionals who signaled to adopt a new variety during the first step, if any of the tweets contained photographic evidence (e.g., tweet with a field photo of a new variety) of new variety adoption, then we considered that the owner of the Twitter account adopted a new variety. At that stage, we combined our photographic evidence with individuals' Twitter messages to determine new variety adoption. Specifically, we considered tweets that explicitly referred to field applications of new varieties, excluding tweets that were related to research objectives or lacked specific descriptions of application objectives. For example, if the tweet included keywords such as "experiment," "study," or "research," then that tweet was not considered an adoption decision. In this way, we identified 43 professionals who adopted a new variety. Finally, to identify professionals who adopted new varieties during our data period yet did not post any photographic evidence on Twitter, we sent out survey questions to professionals (other than 43 professionals whom we already identified as adopters) via Twitter DM. Through this survey, we were able to confirm 42 additional adopters. As a result, our dataset included 85 new variety adopters out of 231 professionals.

Table 1. Descriptive statistics of variables in the sample (n = 231).

	Mean	*SD*	Min	Max
Dependent variable				
New variety adoption (%)	36.79	48.32		
Explanatory variables				
University sports facility managers (group 1) (%)	7.35	26.16		
Professional sports field managers (group 2) (%)	5.19	22.24		
Sod producers (group 3) (%)	9.09	28.81		
Golf course superintendents (group 4) (%)	52.38	50.05		
Public turf managers (group 5) (%)	25.97	43.94		
White (%)	95.67	20.39		
Male (%)	97.40	15.94		
Price[i] (cents per square foot)	36.59	2.58	28.00	54.33
Degree centrality[ii]	0.03	0.04	0.00	0.34
Eigenvector centrality[ii]	0.02	0.09	0.00	0.78
Clustering coefficient	0.54	0.82	0.00	1.00

[i] Source: Sod producer survey (Miller 2022).

[ii] Normalized by dividing each value by the largest value (Zaki et al. 2014).

Table 1 shows descriptive statistics of dependent and independent variables used in our econometric model. The mean of the dependent variable indicated that approximately 37% of our turfgrass professionals adopted a new variety during the study period. The proportion of golf course superintendents (group 4) was the highest at 52.38% among all professional groups, and the proportion of professional sports field managers (group 2) was the lowest at 5.19%. Race and gender variables showed that our participants were mostly white males; among professionals, 95.67% were identified as white and 97.40% were identified as male. The mean sod prices was 36.6 cents/square foot (394.2 cents/square meter), which was comparable to the average market price of warm-season sod at 33.4 cents/square foot (359.1 cents/square meter) (USDA 2020).

Both degree centrality and eigenvector centrality were relatively small, but maximum values were relatively large (0.34 and 0.78 for degree centrality and eigenvector centrality, respectively). This indicated that the overall participants were not active in networking, but that a few highly active (high degree centrality) and influential (high eigenvector centrality) individuals existed in this network. The clustering coefficient shows each individual has a moderate level of clustering behavior. However, similar to eigenvector centrality, the maximum value of the clustering coefficient implied that there were a few individuals who actively interacted within their social circles.

Results

Table 2 reports network descriptive statistics for turfgrass professionals from full and group-wise samples. Of 231 professionals, the total number of connections between individuals in the network (i.e., node) is 990, and the average number of connections between individuals in the network (i.e., tie) is 4.285, indicating that each individual has at least four connections on average. Group degree centrality refers to the degree of networking between groups. The degree of centrality by group shows that golf course superintendents (group 4) are the most active and professional sports field managers (group 2) are the least active during between-group communication. The number of ties in between (off-diagonal elements in matrix) and within (diagonal elements in matrix) groups shows the frequency of between-group and within-group interactions of each group. The between-group and within-group statistics show that golf course superintendents (group 4) have the largest and densest within-network, whereas professional sports field managers (group 2) have the smallest and thinnest within-network. Overall, the network descriptive statistics show that golf course superintendents are the most influential group among all groups because they are the largest and most actively interacting group in this network.

Table 3 shows group-individual eigenvector centrality measures that explain the influence level of each group on individuals, i.e., elements of eigenvector g in Eq. [3], in the network (Bonacich 1991). Among the decision-making professional groups (groups 1–5), golf superintendents (group 4) are the most influential group for individuals in the network, and private researchers and consultants (group 8) are the most active group among advisors (groups 6–8). Tables 2 and 3 show that golf course superintendents are most influential in both between groups and between individual and group networks.

Table 4 reports the results of the Bayesian SAR probit estimation. Parameter estimates are posterior means from the Markov Chain Monte Carlo process with three different chains with 10,000 samples and 1000 burn-in per chain. Gelman-Rubin statistics for all estimates are close to 1, which implies successful Markov Chain Monte Carlo convergences for all parameters (Gelman and Rubin 1992). In our study, adjacency matrix coefficients ρ_1 and ρ_2 are restricted to ensure model convergence. We use the inverse of maximum and minimum eigenvalues as upper and lower bounds for their four-parameter β distribution: $-0.025 < \rho_1 < 0.016$ and $-0.004 < \rho_2 < 0.004$ (LeSage and Pace 2009; Smith and LeSage 2004). To avoid perfect correlation, public turf managers (group 5) are omitted as a reference. All estimations were executed with the R program using the *spatialprobit* package (Wilhelm and de Matos 2013).

Model 1 is the base model with no restriction, and model 2, model 3, and model 4 extend the base model by imposing parameter restrictions to determine the sensitivity of estimates to model specifications. The sensitivity analysis can also show whether potential collinearity between explanatory variables affects the estimation results. Models 2 to 4 are without advisor networking effects ($\beta_{11} = 0$), network structure effects ($\beta_8 = \beta_9 = \beta_{10} = 0$), and both advisor networking and network structure effects ($\beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$), respectively.

Although the posterior log-likelihood values showed that the most restricted model, model 4, best fit to the data, the overall results do not change across models. The negligible differences between models, along with low variance inflation factor (<5) between network structure measures and non-zero (or not close to zero) eigenvalues between adjacency matrices, indicate no serious multicollinearity and specification problems in our probit model. A comparison of results from our alternative models with the base model results also suggests that advisor networking and network structure variables may not be major factors affecting new variety adoption.

Table 2. Network descriptive statistics for turfgrass professionals (n = 231).

Overall network descriptive statistics					
Total number of nodes (individuals in network)					231
Total number of ties (connections between individuals in network)					990
Average degree (number of ties)					4.285
Group degree centrality[i]					
University sports facility managers (group 1)					0.257
Professional sports field managers (group 2)					0.168
Sod producers (group 3)					0.209
Golf course superintendents (group 4)					0.481
Public turf manager (group 5)					0.444
Number of ties: between and within groups					
	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1	24	17	12	24	34
Group 2	17	10	4	10	20
Group 3	12	4	24	23	32
Group 4	24	10	23	320	74
Group 5	34	20	32	74	112

[i] Normalized by the total number of ties from each group, which resulted in values between 0 and 1 (Everett and Borgatti 1999).

Table 3. Descriptive statistics: group-individual dual centrality[i] (n = 401[ii]).

University sports facility managers (group 1)	0.001
Professional sports field managers (group 2)	0.004
Sod producers (group 3)	0.001
Golf course superintendents (group 4)	1.000
Public turf managers (group 5)	0.018
Turf management suppliers (group 6)	0.003
University faculty and professionals (group 7)	0.001
Private researchers and consultants (group 8)	0.419

[i] The group–individual centrality explains the degree of social influence of each group on individuals in the network; the dual centrality measure is normalized by the maximum eigenvalue ranging from 0 to 1 (Bonacich 1991).
[ii] Including 231 turfgrass professionals (groups 1–5) and 170 advisors (groups 6–8).

Results from all four specifications (models 1–4) show that golf course superintendents (group 4), information-intensive networking effects (W_1), and simple networking effects (W_2) are positive and statistically significant at least at the 90% confidence level. Among professional groups (group 5, turfgrass managers for public land, is dropped as the base group), golf course superintendents (group 4) are likely to adopt new varieties. The network descriptive statistics reported in Tables 2 and 3 also show that they are most influential with the highest group-level degree centrality coefficients. The results imply that a highly communicative and influential group is more likely to adopt new technology than other groups (Bandiera and Rasul 2006).

Most, if not all, golf course superintendents would agree that the choice of turf varieties should play a significant role in playability and profitability of a golf course. When selecting the right turf varieties, they need to consider key important factors such as water requirement, stress-tolerance (e.g., salinity and shade), drought resistance, and environmental friendliness (e.g., low requirements of chemical and fertilizer). Golf course superintendents could be more mindful of these factors than other professionals because they have daily interactions with customers (Millington and Wilson 2013), and golf courses attract more foot traffic than any other fields (Cockerham et al. 2000). Therefore, golf course superintendents would be more likely to adopt new varieties, e.g., water-conserving, stress-tolerant, and environmentally friendly varieties, than other professionals. In fact, the US Golf Association and Golf Course Superintendents Association of America provide more than $1 million annually for turfgrass research.

We also find that individuals with more direct connections are more likely to adopt new technology. Insignificant estimates of gender and race variables (β_1 and β_2) show that these individual demographic factors are not important for professionals' new technology adoption decisions, which may be the case because turfgrass professionals are mostly demographically homogeneous (mostly white males, as reported in Table 1) (Santos and Barrett 2008).

From models 1 and 2, although the degree centrality estimate (β_8) shows a strong and positive effect on the new variety adoption, both eigenvector centrality and clustering coefficients (β_9 and β_{10}) are insignificant. The results indicate that individuals with strong social connections (e.g., popular individuals among coworkers) are more likely to adopt a new technology than others, whereas individuals with more influence on the network (e.g., a senior manager of a firm) or a higher cluster tendency (e.g., individuals who primarily interact with their peers) do not show any difference from others in the adoption of new technology.

As discussed, we include the individual-group centrality measure that represents influence from advisor groups (groups 6–8) to each decision-maker in model 1 and model 3 (Bonacich 1991). Accordingly, the corresponding coefficient, β_{11}, indicates how the advisor–decision maker networking affects decision-makers' technology adoption. The statistically insignificant β_{11} suggests three possible reasons. First, advisor groups (groups 6–8) do not actively interact with decision-maker groups (groups 1–5) on average. Second, decision-makers could be skeptical with advisor groups' recommendations of new varieties, especially if the decision-makers are experienced individuals (Conley and Udry 2010). Third, decision-makers may rely more on the information from the internet or online social networking with peers rather than advisors' recommendations (Wood et al. 2014).

As discussed in the methodology section, our study considers matrices W_1 (information-intensive networking) and W_2 (simple networking) representing social learning and herd behavior, respectively. Manski (2004) states that social learning is the process by which each individual sequentially obtains and updates information through the network. The learning effect is typically confounded with non-learning networking effects such as group-level and individual-level similarities, herd behavior, and clustering effects. Thus, after filtering out the non-learning networking effects, the coefficient of information-intensive network (W_1), ρ_1, represents individuals' learning effects from information-intensive networking (Glazer 1991; Golub and Jackson 2010).

The positive and significant ρ_1 from all four models explains that the learning process has significant impact on professionals' adoption decisions. The coefficient of W_2, ρ_2, is also positive and significant, but is smaller than ρ_1, which indicates that mimicking the choice or opinion of others (herd behavior) would also significantly affect an adoption decision, but less effective than information-exchange networking, especially for knowledgeable individuals such as turfgrass professionals (Munshi 2004; Straub 2009).

Table 4. Parameter estimates from spatial autoregressive probit regression (n = 231).

Variable	Parameter	Model 1 (baseline)	Model 2 ($\beta_{11} = 0$)	Model 3 ($\beta_8 = \beta_9 = \beta_{10} = 0$)	Model 4 ($\beta_8 = \beta_9 = \beta_{10} = \beta_{11} = 0$)
Intercept	β_0	1.016	0.974	1.023	1.220
Male	β_1	−0.397	−0.319	0.431	−0.576
White	β_2	0.263	0.239	0.115	0.356
University sports facility managers (group 1)	β_3	0.058	0.161	−0.064	0.245
Professional sports field managers (group 2)	β_4	−0.480	−0.418	−0.585	−0.404
Sod producers (group 3)	β_5	−0.476	−0.392	−0.466	−0.368
Golf course superintendents (group 4)	β_6	0.354*	0.431*	0.398*	0.439**
Sod price	β_7	−0.019	−0.021	−0.038	−0.025
Degree centrality	β_8	7.221***	7.174***		
Eigenvector centrality	β_9	−0.589	−0.405		
Clustering coefficient	β_{10}	−0.151	−0.189		
Networking with advisors	β_{11}	0.005		0.126	
Information-intensive networking (W_1)	ρ_1	0.008*	0.007*	0.007*	0.008*
Simple networking (W_2)	ρ_2	0.002*	0.002*	0.002*	0.001*
Posterior log-likelihood		−229.494	−220.894	−200.391	−198.729

*, **, and *** indicate that the Bayesian estimates do not include zero in the credible interval of 90%, 95%, and 99%, respectively.

Conclusions

Our study investigates the role of social learning in new variety adoption decisions using Twitter data of turfgrass professionals and advisors. To identify the social learning effect, we decompose social networking effects into learning, group-similarities and individual-similarities, clustering, and herd behavior. Bayesian SAR probit models estimate each of the decomposed social networking effects with alternative model specifications.

Our key findings include the following: learning from social networking significantly affects new technology adoption decisions by turf professionals; the learning effect is greater than the herd behavior effect; individuals with close connections (i.e., high degree centrality) are more likely to adopt new technology; large and socially active group (e.g., golf course superintendents) more aggressively adopt new technology than other groups; and decision-makers rely more on information from online social networking than on suggestions from advisors.

Our findings provide useful implications for various horticultural commodity producers and marketers who consider online social networks as marketing tools. They could also provide some insights into developing effective extension programs using social media. Another contribution to the literature might be to propose an empirical procedure that can estimate the effects of social learning on technology adoption using a SAR probit model. Our study demonstrates how the SAR probit model can be used to estimate the social learning effect, whereas the reflection problem, particularly caused by unobserved networking factors, is effectively addressed by directly incorporating adjacency matrices in the model.

Although our study yields several important findings and contributions, there are a few caveats when interpreting them. First, like most datasets used in social network analyses, our dataset does not represent the general population of turfgrass professionals and researchers. Therefore, results from the present study should be interpreted as a case study. Second, the adjacency matrices used during this study are constructed in a SAR framework, yet the fixed social networks could be a strong assumption to reflect the reality (Pinkse and Slade 2010). Third, our choice of weak networking, "reply," may not have been weak enough to represent the herd behavior. For instance, Twitter has other network signals such as "like" and "following," and networking effects of these signals were not able to be tested during the sensitivity analysis of this study because of the limited data availability. Finally, we conclude that larger and more socially active groups are more likely to adopt a new technology than other groups. Although we made our best effort through normalization, large groups might have been socially active because of their size and vice versa, and this simultaneity might have resulted in the reflection problem (Manski 1993).

One possible direction of extending the present study might be to address endogenous adjacency matrices using the exponential random graph model. The exponential random graph model considers each interaction in network as random, thereby allowing the prediction of the network structure in terms of the probability of interaction between individuals (e.g., a probability of person A interacting with person B in the network given the networking characteristics) (Snijders et al. 2006). Then, applying a predicted network structure via exponential random graph model as the Instrumental Variable (IV) estimator could account for the endogeneity problem. One could also apply methodologies that mitigate the selection bias problem. For instance, the Bayesian hierarchical modeling approach with individual-level random effects could account for the unobserved individual-specific attributes such as demographic-specific effects. Unlike the conventional random-effects model, the Bayesian hierarchical approach would have no low degrees of freedom issues caused by an insufficient sample size. Simulating network structure changes caused by policy or environmental shock could also be an interesting research option. For instance, when stakeholders engage more actively with consultants or extension specialists through government programs, the network structure among stakeholders will change and affect stakeholders' decision-making processes through social networks. Finally, applying network structure measures other than centralities could provide more practical policy implications. For example, network measures considering the direction of social interaction could suggest which type of interaction could be the most efficient way to transfer information (e.g., one-way interaction vs. two-way interaction).

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