The Coevolution of Network Structure and Perceived Ease of Use

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Abstract. Perceived Ease of Use (PEoU) is one of the most central constructs in IS research. However, it has been examined only from an individual perspective. This article conceptualizes PEoU as a network construct. Results indicate three things. Firstly, the higher a person's PEoU, the more likely she or he is sought for advice. Secondly, there is a greater likelihood that a person seeks out another person for advice if the other person also seeks out the first person for advice. Thirdly, a person's PEoU will become similar to that of other persons' she or he seeks out for advice.

Keywords: SIENA, Social Network Analysis, Technology Acceptance Model, TAM

1 Introduction

While there are only a few constructs as central in IS research as Perceived Ease of Use (PEoU), research on PEoU has focused the individual perspective only. While an actor's embeddedness in a social network may exert a significant influence on the actor's attitudes, few works acknowledge that an actor's attitudes and behavioral intentions are influenced by that actor's embeddedness in a social network (compare [1]). For example, it is likely that an actor's PEoU influences and is influenced by the PEoU of her or his surrounding peers, which would mean, for example, that if an actor perceives an information system to be easy to use, that perception should spread to her or his neighbors in a social network (and vice versa). Nevertheless, this mutual influence of PEoU has not yet been researched; the reason may be attributable to the fact that, until recently, no adequate statistical methods to test such kind of hypothesis had been developed. Now, however, some new statistical methods allow for the creation of such models.

Research of this kind is of great importance. For example, managers who have to choose which employees should be given further vocational training may wish to consider the employee's embeddedness in a social network.

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Hence, the current work has three main objectives:

1. Conceptualize PEoU as a network construct. In doing so, PEoU should be conceptualized both as an antecedent to network structure and as an outcome of network structure.
2. Propose a model that incorporates PEoU as a network construct.
3. Validate the model empirically.

This article is organized as follows. Section 2, Theory, reviews the related literature and develops four hypotheses. Section 3, Method, describes the study's context, participants, measurement, and modeling approach. Section 4, Results, highlights our findings. Section 5, Discussion, discusses the theoretical and managerial implications of our findings. Section 6, Conclusions, summarizes the results, notes their limitations, and provides some suggestions for further research.

2 Theory

The first part of the literature review highlights the conceptual underpinnings of Perceived Ease of Use. The second part highlights models that examine the evolution of social networks.

2.1 Technology Acceptance and Perceived Ease of Use

Perceived Ease of Use (PEoU) belongs to the most central construct in IS research. It is a core construct of the technology acceptance model (TAM) [2], which is one of the most firmly established models in IS research (compare [3-4]). Perceived Ease of Use is defined as "the degree to which a person believes that using a particular system would be free of effort" [2]. Related constructs can also be found in myriad other theories such as the theory of planned behavior, innovation diffusion theory, and social cognitive theory [5]. In these theories, the related constructs are referred to as, for example, "perceived behavioral control", "self-efficacy", and "complexity." Perceived behavioral control is defined as "the perceived ease or difficulty of performing the behavior and is assumed to reflect experience as well as anticipated future impediments and obstacles" [6]. Complexity is defined as the "opposite of ease of use" [7], that is, "the degree to which an innovation is perceived as relatively difficult to understand and use." Finally, (Computer) Self-Efficacy is defined as "a judgement of one's capability to use a computer. It is not concerned with what one has done in the past, but rather with judgements of what could be done in the future" [8].

Despite the high prominence of these constructs in IS research, the fact that PEoU has been conceptualized only from an individual's perspective (i.e., residing within each individual and isolated from other individuals) leaves a notable gap in the research. The individuals' embeddedness in a social network has been neglected nearly completely (for an exception, see, [1]). Rather, the influence of the other actors on a focal individual is captured by constructs such as "subjective norm," defined as "the person's perception that most people who are important to him think he should or should not perform the behavior in question" [9].

However, the models do not hypothesize how PEoU is influenced by network structure, and how PEoU influences network structure, which leads to the second focus of our literature review.

2.2 Social Network Perspective, Embeddedness and the Evolution of Social Networks

In this paper, we assume that each focal individual (ego) is embedded in a social network of alters (see Figure 1).

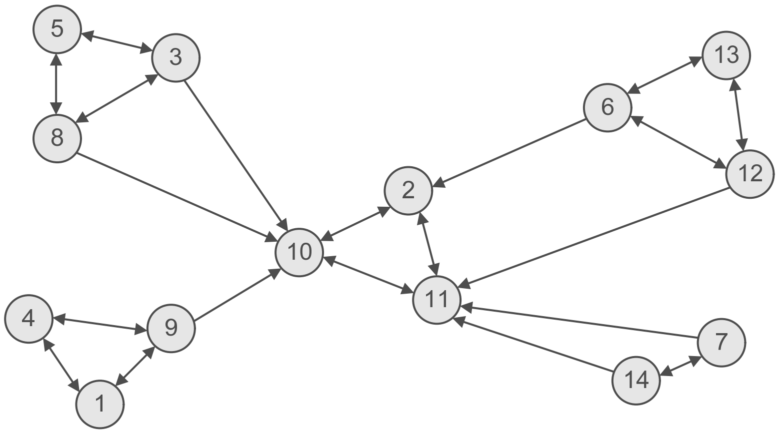

Fig. 1. Social Network

Figure 1 illustrates a networked perspective on PEoU. In the figure, each circle represents an individual. A pair of individuals is connected by an arrow if one actor seeks advice from the other actor.

As we show in the hypotheses development, we assume that PEoU spreads through this social network through a process of contagion. This process of contagion can be modeled with other models that examine the co-evolution of social networks and actor characteristics. Here we review these types of models. Early models examining the evolution of social networks (for an introduction, see [10]) primarily explore how structural characteristics of networks (such as transitivity, reciprocity, and degree-centrality) influence the process of network evolution (see, e.g. [11]).

Recent developments in these types of models (see, e.g. [12]) now also allow for the integration of several actor characteristics, which are permitted to co-evolve with the social network over time (e.g. [13]) so that the social network (and the actor characteristics) can be dependent and independent variables concurrently. Hence, these models allow for statistical tests of causal relationships between network structure and actor characteristics (such as Perceived Ease of Use) that were not previously possible.

2.3 Hypotheses Development

We structure the development of our research hypotheses in two parts. In the first part, we propose two hypotheses regarding the co-evolution of social network and Perceived Ease of Use. The first of these addresses Perceived Ease of Use as an antecedent to network evolution. The second explains Perceived Ease of Use as an outcome of network structure. In the second part of our hypotheses development, we propose two hypotheses that examine the effects of endogenous[1] network variables on the process of network evolution. These two variables serve as control variables in our study.

Perceived Ease of Use. We begin with a hypothesis that considers Perceived Ease of Use as an antecedent to network structure. Generally, a person who perceives a computer system to be easy to use has a high expertise in using the system (compare [14]). Furthermore, the greater a person's expertise, the more likely he or she is sought out for advice by other people [15]. In summary,

Hypothesis 1 (PEoU alter): The higher a person's Perceived Ease of Use, the more likely she or he is sought out for advice.

The second hypothesis concerns Perceived Ease of Use as an outcome of network structure, and is based on social influence theories, one of the most prominent being social comparison theory (e.g. [16-17]). Social comparison theory assumes that individuals compare themselves with their surrounding peers. During these comparisons, they adapt their individual attributes so that they become more like their peers. In a similar vein, we assume in this paper that people compare their Perceived Ease of Use to each other. We expect that people who observe others with a high PEoU of a system will perceive the system easier to use for themselves. Conversely, we expect that people who observe others that perceive a system difficult to use will perceive the system difficult to use for themselves. Hence,

Hypothesis 2 (PEoU similarity): Over time, the likelihood that a person's Perceived Ease of Use will become similar to that of other persons' she or he seeks out for advice is greater than a random change in Perceived Ease of Use.

Endogenous Network Effects. We next propose two hypotheses that examine the effects of endogenous network variables on the process of network evolution. These two variables serve as control variables. As our first endogenous network hypothesis, we hypothesize that people do not seek advice for free. Rather, building and maintaining relationships for seeking advice is associated with some cost (c.f. [18]). Consequently, people who are embedded in an advice network with many partners are less likely to seek out new people for advice than are people who have only a few con-

[1] In this paper, we use the term "endogenous" in the sense of Contractor et al. (2006), that is, endogenous variables do not incorporate factors other than the focal relationship itself. In particular, they may not include attributes of the actors in the network.

tacts. Numerous studies that examine the scale-free property of social networks (e.g. [19]) and models of dynamic network evolution (e.g. [13]) support this finding. Hence,

Hypothesis 3 (Density): The higher the number of a person's partners for seeking advice, the lower the likelihood that he or she will seek out new partners for advice.

As a second endogenous network hypothesis we hypothesize mutual/ reciprocated ties, that is, if person *i* seeks out person *j* for advice, person *j* should also seek out person *i* for advice. Several theories explain reciprocal ties, including social exchange theory [20], resource dependency theory [21], and network exchange theory [22], compare [23]. For example, social exchange theory assumes that relationships are built through an individual cost-benefit analysis: the benefits for an individual are the positive elements of a relationship such as advice, support, or friendship; the costs are the effort required to maintain a relationship. In general, scholars agree that relationships evolve over time into trusting, loyal, and mutual commitments as actors obey certain rules of exchange. Reciprocity is probably the best-known exchange rule [24]; it means, in theory, giving advice to someone is considered to be a previous investment in a relationship that must be reciprocated. However, some researchers state that relationships in advice networks tend to be nonreciprocating/ asymmetric, that is, a less well-informed actor is more likely to seek advice from a more well-informed actor than vice versa (e.g. [15], [25-26]). One possible explanation for non-reciprocal dyads is actors striving for social status, compare [25]. Actors that have acquired a certain social status by being sought out for advice will attempt to preserve this status advantage by seeking advice from third parties rather than from the actors that have sought them out for advice. Another possible explanation for non-reciprocated dyads is that actors sought out for advice by a certain individual *i* will not seek advice from this particular individual, as they doubt the individual's capabilities.

Nevertheless, we assume that the last two explanations do not hold for this study. First, asking someone for advice in the learning situation of the study was not associated with a loss of status. Furthermore, people who sought out others for advice were not perceived to be unknowledgeable. Hence,

Hypothesis 4 (Reciprocity): There is a greater likelihood that a person seeks out another person for advice if the other person also seeks out the first person for advice.

3 Method

To test the proposed hypotheses, we used data collected during a June 2010 PhD course on social network analysis taught in the IS department of a leading research university.

3.1 Context

The aim of the five-day course was to familiarize students with a software system for longitudinal social network analysis that had been co-developed by one of the authors. Morning sessions of the course were devoted to training; in the afternoons, when students applied the software, they were free to seek advice from other course participants. Most students were first-year PhD students. Rather than grades, a certificate was awarded for attendance, and participation in the course was voluntary. Three participants had extensive experience with the social network analysis software taught in the course.

3.2 Participants

The unit of analysis in our study is the individual student. The course had 15 participants, one of whom dropped out during the course. Before our final analysis, the student who dropped out was excluded due to an extensive amount of missing data. Participation in the course formed an appropriate boundary for our study because the class members interacted in the context of the system that bound them with interdependent processes and a shared symbol system [1]. There was one woman among the 14 participants, which is typical for a course taught in an IS department. The average age of the respondents was 32.46 years, with a standard deviation of 7.95 years. The youngest participant was 24 years old; the oldest was 48. Although the sample size is quite small (n = 14), it is sufficient for the proposed methodology since the model has only 3 predictors.

3.3 Measurement

Like Sykes et al. [1], we collected data with a survey administered before students used the new system immediately after the first training session. Furthermore, we collected data on the third and on the fifth days at the conclusion of the afternoon sessions.

We measured Perceived Ease of Use with 5 items (compare [2], [5], [27]): (1) Learning to operate <the system> is easy for me; (2) I find it easy to get <the system> to do what I want it to do; (3) It is easy for me to become skillful at using <the system>; (4) I find <the system> easy to use; (5) My interaction with <the system> would be clear and understandable. All items were measured using seven-point semantic differentials anchored with “strongly disagree” and “strongly agree” as well as numbers from -3 to +3. Later, we aggregated the 5 items to a single value for PEoU.

Furthermore, we asked the following question: During the last <n> days of the seminar, how often and for how long did you seek advice from the following persons? We used a seven-point semantic differential anchored with <never> to <very long and often> for this question. We later dichotomized the answers as described in Sykes et al. [1]. In the following section, $X(t) = X_{ij}(t)$ denotes an $n \times n$ adjacency matrix, where $X_{ij} = 1(0)$ represents a tie (no tie) from actor i to actor j ($i,j = 1,\ldots,n$) in period t, that is, player i responded at least “0” on the semantic differential.

3.4 Model

To examine the dynamic co-evolution of network structure and Perceived Ease of Use, we employed a stochastic actor-driven modeling approach proposed by Snijders, e.g. [13], [28-29]. The first application of this methodology in IS research is a recent article by Putzke et al. [30].

The advantage of Snijders’ methodology is that the same variable can be interpreted concurrently as both an independent and a dependent variable, as we show in the following paragraphs. This makes it possible to establish a causal relationship between structural network variables and PEoU.

Snijders models the co-evolution of network structure and actor characteristics as a continuous-time Markov process $Y(t) = (X(t), Z_{h1}(t),\ldots, Z_h(t))$ on the space of adjacency matrices $X(t)$ as well as actors’ characteristics Z_{hi} $(h = 1,\ldots,H)$ (in this case, PEoU). To derive a transition matrix between two states $y(t_m)$ and $y(t_{m+1})$, Snijders decomposes each change between the states into so-called “micro steps.” Micro steps are randomly determined moments in time whose queue time follows an exponential distribution with rate parameters $\lambda_i^{[X]}$ and $\lambda_i^{[Z_h]}$ that we assume to be constant and independent between actors. At these randomly determined moments in time, one of the actors has the opportunity either to: change a tie variable X_{ij} (i.e. $\hat{y} = (x(i \Rightarrow j), z)$); change his or her own characteristics Z_{hi} by δ (i.e. $\hat{y} = (x, z(i \updownarrow_h \delta))$); or change nothing (i.e. $\hat{y} = y$). These changes occur with probabilities $p = (x(i \Rightarrow j) | , x(t), z(t))$ and $p = (z(i \updownarrow_h \delta) | \, x, z)$ respectively. Whereas $p = (x(i \Rightarrow j) | , x(t), z(t))$ denotes the probability that actor i changes its tie to actor j (conditioned on all other ties being constant, and given actor characteristics), $p = (z(i \updownarrow_h \delta) | \, x, z)$ denotes the probability that actor i’s characteristic h will decrease or increase by δ. To obtain transition intensities, Snijders multiplies the rate functions by the probabilities of an actual change taking place, which leads to the transition matrix

$$q_{ij} = \begin{cases} \lambda_i^{[X]}(y)\, p\left(x(\mathrm{i} \Rightarrow \mathrm{j}) \middle| x, z\right) & \text{if } \hat{\mathrm{y}} = \left(x(\mathrm{i} \Rightarrow j), z\right), \\ \lambda_i^{[Z_h]}(y)\, p\left(z(\mathrm{i} \updownarrow_{\mathrm{h}} \delta) \middle| x, z\right) & \text{if } \hat{\mathrm{y}} = \left(x, z(\mathrm{i} \updownarrow_{\mathrm{h}} \delta)\right), \\ -\sum_i \left\{ \sum_{j \neq i} q\left(y; \left(x(\mathrm{i} \Rightarrow \mathrm{j}), z\right)\right) + \sum_{\delta \in \{-1,1\}} q\left(y; \left(x, z(\mathrm{i} \updownarrow_{\mathrm{h}} \delta)\right)\right) \right\} & \text{if } \hat{\mathrm{y}} = \mathrm{y}, \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

To estimate the full model, the change probabilities $p = (x(i \Rightarrow j)|, x(t), z(t))$ and $p = (z(i \updownarrow_h \delta)| \; x, z)$ have to be specified, which we do as discrete choice models in multinomial logit form (cf. McFadden, 1974). That is

$$p = \left(x(i \Rightarrow j)|, x(t), z(t)\right) = \frac{e^{u^{[X]}}(\beta, x(i \Rightarrow j)(t), z(t))}{\sum_k e^{u^{[X]}}(\beta, x(i \Rightarrow j)(t), z(t))} \tag{2}$$

where $u^{[x]}$ denotes the deterministic part of a utility function that actor i attributes to the network configuration. For example, a utility function that allows only a test of H3 (density) and H4 (reciprocity) might be defined as

$$u_i^{[X]}\left(\beta^{[X]}, y\right) = \beta^{density} \sum_j x_{ij} + \beta^{reciprocity} \sum_j x_{ij} x_{ji} \tag{3}$$

Analogously, the formulas for the behavioral evolution of PEoU can be derived (for a more detailed discussion, see [13]).

The following effects were included in the utility functions:[2] The *PEoU-alter* effect was measured as $\sum_j x_{ij} \, PEoU_j$ (cf. hypotheses 1), that is, actor i's utility function $u^{[x]}$ increases by actor j's PEoU if actor i seeks advice from actor j (i.e. $x_{ji} = 1$). Hence, a positive parameter $\beta^{PEoU\ alter}$ indicates that students with a higher PEoU are more likely to be sought out for advice than are students with a lower PEoU.

PEoU average similarity (c.f. hypothesis 2) was measured as

$$\frac{1}{x_{i+}} \sum_j x_{ij} \left(\frac{max_{ij}|PEoU_i - PEoU_j| - |PEoU_i - PEoU_j|}{max_{ij}|PEoU_i - PEoU_j|} - \overline{\frac{max_{ij}|PEoU_i - PEoU_j| - |PEoU_i - PEoU_j|}{max_{ij}|PEoU_i - PEoU_j|}} \right) \tag{4}$$

where $\overline{\frac{max_{ij}|PEoU_i - PEoU_j| - |PEoU_i - PEoU_j|}{max_{ij}|PEoU_i - PEoU_j|}}$ is the mean of all similarity scores $\frac{max_{ij}|PEoU_i - PEoU_j| - |PEoU_i - PEoU_j|}{max_{ij}|PEoU_i - PEoU_j|}$.

The similarity score between actor i and actor j calculates the difference between the PEoU of the two actors $|PEoU_i - PEoU_j|$ (in absolute values) and standardizes this difference by the range of all actors' PEoU $max_{ij} |PEoU_i - PEoU_j|$. Hence a positive parameter $\beta^{PEoU\ similarity}$ indicates that an actor's PEoU tends to become similar to the PEoU of those actors she or he seeks out for advice. However, the total influence of the actor she or he seeks out for advice is the same regardless of their number.

A general *drive toward high PEoU* (linear shape effect) was measured as $PEoU_i$. This effect was added as an additional control variable, since course participants became more familiar with the software during the course and hence would be expected to perceive the software to be easier to use over time.

General tendency to seek advice from alters (density/outdegree effect) is measured as

[2] See Snijders et al. (2007) for more information about the measures.

$$\sum_j x_{ij} \tag{5}$$

(cf. hypothesis 3), that is, actor *i*'s utility function $u^{[x]}$ increases by value 1 if actor *i* seeks out actor *j* for advice, because the corresponding value in the adjacency matrix x_{ij} equals 1 if actor *i* seeks advice from actor *j* (and is 0 otherwise). Consequently, a negative parameter $\beta^{outdegree}$ indicates that actor *i* does not seek advice randomly, but that each occasion of seeking advice is associated with some "cost" for actor *i*.

Number of mutual ties (reciprocity) is measured as

$$\sum_j x_{ij}x_{ji} \tag{6}$$

(cf. hypothesis 4), that is, actor *i*'s utility function $u^{[x]}$ increases by value 1 only if actor *i* seeks advice from actor *j* (x_{ij} = 1) and actor *j* seeks advice from actor *i* (x_{ji} = 1). If one of these ties is missing (i.e. x_{ij} = 0 or x_{ji} = 0), the product will equal 0. Consequently, a positive parameter $\beta^{reciprocity}$ indicates a greater likelihood that actor *i* seeks advice from actor *j* if actor *j* also seeks advice from student *i*.

4 Results

We conducted a nested model comparison to test the proposed hypothesis, see [29]. All models were estimated using RSiena and RSienaTest 1.0.12.186. In a series of Neyman-Rao tests, we compared a model that allows both PEoU effects to vary freely against a baseline model that restricts one (or both) PEoU parameters to zero, but includes all control variables. We report no measure of explained variation because there are, as yet, no satisfactory measures for this stochastic actor-driven modeling approach.

Table 1. Model Results

	Beta	s.d.	t-value	p-value
Network Dynamics				
Rate Parameter (t=1)	2.310	.837	2.760	.003
Rate Parameter (t=2)	1.334	.468	2.850	.002
Outdegree	-1.697	.381	-4.454	<.001
Reciprocity	3.279	.739	4.437	<.001
PEoU alter	0.120	.053	2.264	.011
Behavior Dynamics				
Rate Parameter (t=1)	5.772	2.3642	2,441	.007
Rate Parameter (t=2)	2.780	.984	2.825	.002
PEoU linear shape	2.498	5.999	0.416	.339
PEoU average similarity	295.900	.444	666.441	<.001

The series of Neyman-Rao tests indicate that the inclusion of both PEoU effects in the model (see Table 1) at the same time increases model fit, and that the increased model fit can be attributed to both effects, that is, to PEoU alter ($\chi^2 = 6.642$; *d.f* .= 1; $p < .01$) as well as to PEoU similarity ($\chi^2 = 7.223$; *d.f.* = 1; $p < .01$).

Furthermore, both effects are found to be statistically significant and in the expected direction. Hence, Hypothesis 1 and Hypothesis 2 are supported, and we can conclude that 1) students are more likely to seek advice from a partner that perceives the system as easy to use, and 2) that the students' PEoU over time tends to become similar to those of their surrounding peers.

Concerning the control variables (Hypothesis 3 and Hypothesis 4), the results are in line with our expectations. The negative outdegree effects indicate that seeking ties is associated with some costs and the positive reciprocity effect indicates that students are more likely to seek advice from students who sought advice from them. However, the linear shape effect turns out to be positive but non-significant. Hence, there is limited support for the proposition that course participants perceived the software to be easier to use over time.

Further results can be found in the Appendix, where Table 2 provides the correlations of estimates and Table 3 highlights the tie changes between subsequent observations. Indeed, the Jaccard coefficients (see Table 3) fall within acceptable levels.

We further tested for time heterogeneity in parameters between both time periods, compare [31]. In the original model, the objective function was defined as:

$$f_i^{net}(x) = \sum_k \beta_k^{net} s_{ik}^{net}(x), \tag{7}$$

where $s_{ik}^{net}(x)$ were the effects as defined above. This means that all parameters β were assumed to be stable over time. To test for time heterogeneity in the parameters, the objective function was defined as:

$$f_{ij}^{(a)}(x) = \sum_k \left(\beta_k + \delta_k^{(a)} h_k^{(a)}\right) s_{ik}\left(x(i \leadsto j)\right) \tag{8}$$

where $h_k^{(a)}$ is a vector of time dummies and $\delta_k^{(a)}$ is the time dummy interacted effect parameter for effect k in period a. The dummy variables $\delta_k^{(1)}$ were assumed to be 0 for all k, so that the first period is considered to be the base period. A joint score test for parameter heterogeneity is then given as:

$$H_0: \delta_k^{(a)} = 0 \; \forall k, a \tag{9}$$

$$H_1: \delta_k^{(a)} \neq 0 \; for\ some\ k, a \tag{10}$$

For the further estimation of the test, see [31].

The results of a joint test of dummy parameters for all effects (outdegree, reciprocity, PEoU alter, PEoU linear shape, PEoU similarity) revealed that it is not necessary to introduce time dummies for a particular effect ($p = .746$).

Further, we assessed goodness of fit using the indegree distribution as auxiliary statistic (see Figure 2) of a Monte Carlo Mahalanobis Distance Test (compare [32]). Results indicate that goodness of fit is good (Mahalanobis Distance = 16.384; $p = .173$).

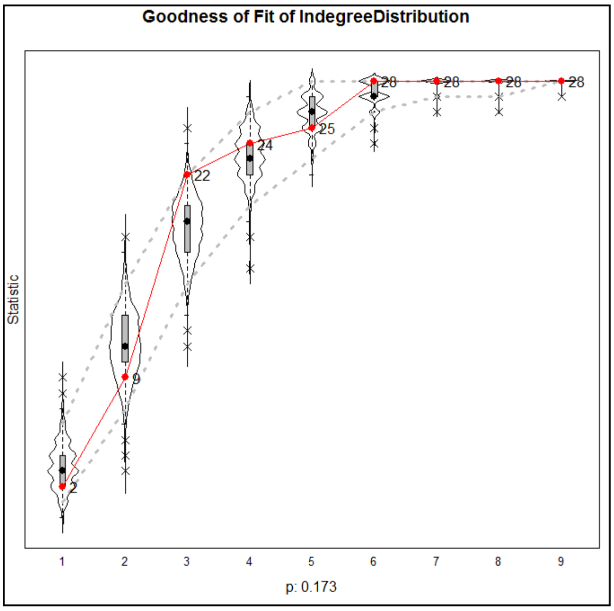

Fig. 2. Goodness of Fit of Indegree Distribution

5 Discussion

In this study, we theorized PEoU as a network construct. In particular, we hypothesized that people are more likely to seek advice from a partner who perceives a system as easy to use. Furthermore, we hypothesized that people's PEoU over time tends to become similar to that of their surrounding peers. The empirical study lent support to both hypotheses.

5.1 Theoretical Contributions and Implications

The paper contributes to IS research in several ways. First, the model is a fundamental shift in our understanding of PEoU. Whereas PEoU used to be examined from an individual perspective in structural equation models, the results show that PEoU is an antecedent as well as an outcome of network structure. Future research should, therefore, take a network perspective on PEoU.

Second, the paper introduced a new methodology from sociology into IS literature. Apart from [30], it is the first paper in IS research that uses a methodology that can examine the co-evolution of actor characteristics and social network. However, this paper exceeds the paper [30] as it tests for time heterogeneity and reports goodness of fit using the indegree distribution as auxiliary statistic of a Monte Carlo Mahalanobis Distance Test.

5.2 Practical Implications

In addition to the theoretical insights, this study also has some implications for practitioners. Results showed that people's PEoU tends over time to become similar to that of their surrounding peers, which means that managers should not regard PEoU as a construct only on the individual level. Rather, managers should examine each individual's embeddedness in a social network before selecting who will take part in a system training course. With the careful selection of individuals, PEoU will spread through the network and, as a consequence, less people will need formal training courses. This will result in cost savings and enhanced organizational performance. This study offered a practical insight that the selection of individuals for training courses should be driven not only by their personal characteristics, but also to some extent by their position in the social network.

Another managerial implication is that managers should pay special attention to the structure of the social networks within and between organizational units when seeking to improve performance outcomes through information systems. Only active management of such networks will optimize network flow and assure that PEoU will spread through the network. Enhancing the level of PEoU in such a way may also prove useful for reducing IT resistance in enterprise systems implementation projects.

Finally, this paper introduced a new methodology from sociology into the IS literature. The proposed methodology can be applied by IS practitioners in a variety of different contexts. For example, practitioners can use the proposed methodology for link prediction (e.g., on social networking platforms).

6 Conclusions

In this article, we conceptualized PEoU as a network construct. Our results indicate that people are more likely to be sought out for advice the higher their PEoU. Furthermore, there is a greater likelihood that a person seeks out another person for advice if the other person also seeks out the first person for advice. Finally, we found that a person's PEoU will become similar to that of other persons' she or he seeks out for advice.

Of course, as with any empirical study, ours is subject to some limitations that could be seen as affecting the rigor and relevance.

First, we examined a single construct from TAM only. We neglected Perceived Usefulness as well as the user's Behavioral Intention to use a system. Future research should examine these constructs in more detail. The proposed methodology offers an interesting way to examine the co-evolution of social networks and these two constructs.

Second, we examined only one type of network (i.e., the advice network). However, there may be other networks that influence an actor's PEoU, such as a friendship network or acquaintance network. Future research should examine related questions with networks other than the advice networks.

There are several fruitful areas where the methodology can be employed in IS research. For example, future research can examine the adoption of information technologies taking a network perspective. Basically, the method is appropriate for various types of analyses that examine the co-evolution of social network and actor characteristics. Our hope is that our research will assist others in conducting these types of studies and form the basis for substantial future research into the co-evolution of social networks, attitudes, and behavioral intentions.

7 Appendix

Table 2. Correlations of Estimates

Rate Parameter (t=1)	1								
Rate Parameter (t=2)	-0.068	1							
Outdegree	-0.292	-0.138	1						
Reciprocity	0.046	0.017	-0.597	1					
PEoU alter	0.004	0.035	-0.467	0.417	1				
Rate Parameter (t=1)	-0.202	0.085	0.040	-0.046	0.019	1			
Rate Parameter (t=2)	-0.155	0.101	-0.019	0.031	0.065	0.560	1		
PEoU linear shape	0.193	-0.129	0.003	0.041	-0.073	-0.826	-0.699	1	
PEoU average similarity	-0.195	-0.016	0.029	0.019	-0.115	-0.205	0.012	0.070	1

Table 3. Tie changes between subsequent observations

	0 => 0	0 => 1	1 => 0	1 => 1	Jaccard Index
from period 1 to period 2	155	13	2	12	.444
from period 2 to period 3	147	10	2	23	.657

References

1. Sykes, T.A., Venkatesh, V., Gosain, S.: Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees' System Use. MIS Quarterly 33, 371-393 (2009)
2. Davis, F.D.: Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly 13, 319-340 (1989)
3. Hu, P.J., Chau, P.Y.K., Sheng, O.R.L., Tam, K.Y.: Examining the technology acceptance model using physician acceptance of telemedicine technology. Journal of Management Information Systems 16 (2), 91-112 (1999)
4. Venkatesh, V.: Where To Go From Here? Thoughts on Future Directions for Research on Individual-Level Technology Adoption with a Focus on Decision Making*. Decision Sciences 37 (4), 497-518 (2006)
5. Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D.: User acceptance of information technology: Toward a unified view. MIS Quarterly 27, 425-478 (2003)
6. Ajzen, I.: The Theory of Planned Behavior. Organ Behav Hum Dec 50, 179-211 (1991)

7. Thompson, R.L., Higgins, C.A., Howell, J.M.: Personal Computing - toward a Conceptual-Model of Utilization. MIS Quarterly 15, 125-143 (1991)
8. Compeau, D.R., Higgins, C.A.: Computer Self-Efficacy: Development of a Measure and Initial Test. MIS Quarterly 19, 189-211 (1995)
9. Fishbein, M., Ajzen, I.: Belief, attitude, intention and behaviour: An introduction to theory and research. Addison-Wesley, Reading, MA (1975)
10. Doreian, P., Stokman, F.N.: Evolution of social networks, Vol. 1. Routledge (1997)
11. Wasserman, S., Pattison, P.: Logit models and logistic regressions for social networks .1. An introduction to Markov graphs and p. Psychometrika 61, 401-425 (1996)
12. Robins, G., Snijders, T., Wang, P., Handcock, M., Pattison, P.: Recent developments in exponential random graph (p*) models for social networks. Soc Networks 29, 192-215 (2007)
13. Snijders, T.A.B., Steglich, C.E.G., Schweinberger, M.: Modeling the co-evolution of networks and behavior. In: Montford, K.v., Oud, H., Satorra, A. (eds.): Longitudinal models in the behavioral and related sciences. Lawrence Earlbaum, Newark, NJ (2007)
14. Li, X., Troutt, M.D., Brandyberry, A., Wang, T.: Decision factors for the adoption and continued use of online direct sales channels among SMEs. Journal of the Association for Information Systems 12 (4) (2011)
15. Nebus, J.: Building collegial information networks: A theory of advice network generation. Academy of Management Review 31 (3), 615-637 (2006)
16. Festinger, L.: A theory of social comparison processes. Human Relations 7, 117-140 (1954)
17. Felps, W., Mitchell, T.R., Hekman, D.R., Lee, T.W., Holtom, B.C., Harman, W.S.: Turnover Contagion: How Coworkers' Job Embeddedness and Job Search Behaviors Influence Quitting. Academy of Management Journal 52 (3), 545-561 (2009)
18. Bolton, P., Dewatripont, M.: The Firm as a Communication-Network. Quarterly Journal of Economics 109 (4), 809-839 (1994)
19. Barabasi, A.L., Albert, R.: Emergence of scaling in random networks. Science 286, 509-512 (1999)
20. Blau, P.M.: Exchange and power in social life. Transaction Publishers, New Brunswick, New Jersey (1992)
21. Pfeffer, J., Salancik, G.R.: The external control of organizations: A resource dependence perspective. Stanford University Press, Stanford, CA (2003)
22. Willer, D.: Network exchange theory. Praeger Publishers, Westport, CT (1999)
23. Contractor, N.S., Wasserman, S., Faust, K.: Testing Multitheoretical, Multilevel Hypotheses about Organizational Networks: An Analytic Framework and Empirical Example. The Academy of Management Review 31, 681-703 (2006)
24. Cropanzano, R., Mitchell, M.S.: Social exchange theory: An interdisciplinary review. J Manage 31, 874-900 (2005)
25. Agneessens, F., Wittek, R.: Where do intra-organizational advice relations come from? The role of informal status and social capital in social exchange. Soc Networks (in press)
26. Carley, K.M., Krackhardt, D.: Cognitive inconsistencies and non-symmetric friendship. Soc Networks 18, 1-27 (1996)
27. Davis, F.D., Bagozzi, R.P., Warshaw, P.R.: User Acceptance of Computer-Technology - a Comparison of 2 Theoretical-Models. Manage Sci 35, 982-1003 (1989)
28. Snijders, T.A.B.: Stochastic Actor-oriented Models for Network Change. Journal of Mathematical Sociology 21, 149-172 (1996)
29. Snijders, T.A.B., van de Bunt, G.G., Steglich, C.E.G.: Introduction to Stochastic Actor-Based Models for Network Dynamics. Soc Networks 32, 44-60 (2010)

30. Putzke, J., Schoder, D., Fischbach, K., Gloor, P.A.: The Evolution of Interaction Networks in Massively Multiplayer Online Games. Journal of the Association for Information Systems 11 (2010)
31. Lospinoso, J.A., Schweinberger, M., Snijders, T.A.B., Ripley, R.M.: Assessing and accounting for time heterogeneity in stochastic actor oriented models. Advances in Data Analysis and Classification 147-176 (2011)
32. Lospinoso, J.A., Snijders, T.A.B.: Goodness of fit for Stochastic Actor Oriented Models. Sunbelt XXXI, St. Pete's Beach, Florida (2011)