THE IMPACT OF NETWORK STRUCTURAL POSITION ON THE CONTRIBUTORY INFLUENCE OF ATTITUDE AND SUBJECTIVE NORM ON BEHAVIORAL INTENTION: A MULTILEVEL TEST

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DEDICATION

To Michael, who alone carried the weight of our world on his back during the times that I could not share the load. To Lauren, Dugan, and baby Jack. To Theory and Practice. Having all of you in my life motivates me to maintain balance. Thank you.

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ABSTRACT

Within contemporary views of attitude formation and change, two sources of influence are assumed to be available to the decision-maker when faced with making a behavioral decision. The first source represents information about consequences of engaging in the behavior and it is based on an individual's attitude. The second is based on normative information about the opinions held by others. Both attitudinal and normative influence can contribute to decision-outcomes, but there is little known about what factors impact the relative contribution of one over the other. In addition to individual level perceptions of a behavior, the context in which a decision is made also influences how individuals make behavioral decisions. The Structural Theory of Social Influence (SSI) proposes that network position, one of many contextual properties, explains how individuals weigh information from both attitudinal and normative sources (Friedkin, 1998). A multilevel test of this explanation is presented. Micro-level variables were based on individual level perceptions of attitude and subjective norm. A decision context was measured by social network analysis to create the macro-level variable of network position. This study focused on a decision context that was constructed of faculty and their behavioral intentions regarding a set of teaching behaviors. The results from a cross-level test (between the macro- and micro-level variables) suggest that network position does not explain variation attitudinal influence. These results are discussed in terms of the SSI and in how they inform diffusion processes. It is proposed that a theory of the balance between attitudinal and normative influence should include individual, behavioral, as well as structural level predictors of interpersonal influence.

CHAPTER 1: UNDERSTANDING SOCIAL INFLUENCE

The use of technology is quickly becoming an expected instructional practice. Technology presents the opportunity to expand the methods used to communicate with students as well as to generate instructional materials that are not replicable within traditional face-to-face classrooms. How do new practices like use of instructional technology spread within a profession? The spread is uneven, with some institutions more likely to encourage new practices, and some subgroups within those institutions more likely to adopt them.

Adoption of new technology is, for faculty, an individual decision, but this decision is clearly shaped by institutional factors (Bradburn & Zimbler, 2002). Multilevel perspectives are beneficial to understanding how individuals make behavioral decisions (Kashy & Kenny, 2000; Monge & Contractor, 2001; Price, Ritchie, & Eulau, 1991). For instance, by using variables at the individual (micro) and institutional (macro) levels, the national study of distance education adoption represents a multilevel approach to understanding how individuals make decisions within a larger social context.

At the individual level, two sources of information are expected to influence decision outcomes (Ajzen & Fishbein, 1980; Bandura, 1986; Scott & Scott, 1982). The theory of reasoned action (TRA), a useful and well-supported theory of behavioral intentions, conceptualizes these sources as an evaluation about performing a particular behavior, labeled as an individual's attitude, and normative information about the opinions held by others, labeled as subjective norm. There is substantial evidence that these two variables predict behavioral intentions (Sheppard, Hartwick, & Warshaw, 1988), and that the relative contribution each predictor has over the formation of behavioral intention varies across individuals (Hedeker, Flay, & Petraitis, 1996). Information is the basis for both sources of influence; the difference between them lies in the type of information used: attitudinal influence is based on facts and evidence about the behavioral object and normative influence is based on the preferences and actions of other individuals that populate the decision context.

Diffusion of innovations theory reflects a multilevel perspective because it uses both individual and contextual influences to explain adoption behavior (Rogers, 1995). Individual-level decision processes occur at a micro level of analysis and contextual influences occur at a macro level of analysis. Individuals who share group membership or a common interest in a diffusing innovation create diffusion contexts that consist of networks of social ties. Diffusion of innovations theory predicts the spread of adoption throughout this social structure; perceptions about performing a behavior are located at the micro level and properties of the diffusion context are located at the macro level. Individuals occupy positions within diffusion contexts, and these positions hold consequences for the flow of influence among social ties.

Centrality is a key network position to diffusion outcomes, and individuals who occupy this position are called 'opinion leaders'. In multilevel terms, opinion leaders exist at a macro level because this role is based on network location. Influence processes occur through the impact of opinion leaders on individual decisions. This represents a cross-level interaction between macro and micro level variables. The theory proposes that opinion leaders shape diffusion outcomes by both attitudinal and normative influence, either by providing information about an innovation or by serving as a role model for others to emulate.

When it comes to explaining how individuals come to behavioral decisions, the TRA suggest two sources of influences (attitudinal and normative), and these sources vary at the individual level. Diffusion of innovations theory adds a structural predictor of individual behavioral decisions, which models contexts in which individuals make adoption decisions. However, these theories do not specify conditions that influence the relative contribution of attitudinal and normative influence in the formation of behavioral intentions. Therefore, a question remains about what factors shape the decision process.

The structural theory of social influence (SSI) offers one explanation for how individuals weigh the information provided by attitudinal and normative influence when making a behavioral decision. This theory contains elements of both the TRA and diffusion of innovations theory. Similar to the TRA, the SSI combines individual level variables that capture sources of influence. Contextual level variables are used to describe individual network positions, a feature that is similar to diffusion of innovations theory. The SSI offers an explanation of individual behavioral choice within a multilevel structure. The theory stipulates that network position, a macro level predictor, influences the way individuals make decisions (Friedkin, 1998). In particular, the theory assumes that structural centrality (a macro level variable) predicts the weights individuals place on attitudinal influences (a micro level variable). This theory presents one explanation for how individuals weigh different sources of influence when making behavioral decisions.

This dissertation reports a test of one assumption within the SSI by applying a multilevel model that blends multiple theories to understand the role of interpersonal influence on individual behavioral choice. The population consisted of instructors at a Carnegie Research 1 institution, and each source of influence, attitude and subjective norm, was assessed on behavioral intentions to enact a set of teaching practices, including the use of instructional technology.

Chapter 2 discusses the predictors of human behavior, organized into micro, macro, and multilevel levels of analysis. Chapter 3 describes the methods and research design used in this study. Results are discussed in Chapter 4, which are interpreted in light of other possible predictors of the relative weight between informational and normative influence in Chapter 5.

CHAPTER 2: MULTILEVEL PREDICTORS OF BEHAVIOR

Variables relevant to behavioral choice appear at micro and macro levels of analysis. For example, dyads are macro-units that are constituted of two interlocutors, the micro-units. Other examples include classes (macro-unit) and students (micro-unit), organizations (macro-unit) and departments (micro-unit), and individuals (macro-unit) and observations (micro-unit). Any number of variables can appear at each level. Within diffusion contexts, research can include individuals as micro-units and organizations as macro-units: Micro-unit attributes may include the variables of innovativeness, adoption rate, and perceptions of an innovation; macro-unit attributes may include variables such as organizational size, management style, or absorptive capacity. The following review presents micro-, macro-, and multilevel perspectives of individual level behavior and interpersonal influence. This section concludes with the rational for this investigation.

Micro Level Perspectives

Micro level approaches to predicting behavior predominately focus on individuals. A large body of evidence supports the role of individual perceptions on behavioral outcomes (Agarwal & Prasad, 1997; Ajzen & Fishbein, 1980; Davis, Bagozzi, & Warshaw, 1989; DeSanctis & Poole, 1994; Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Jackson, Chow, & Leitch, 1997; Jayasuriya, 1998; Lewis & Seibold, 1996; Sheppard et al., 1988). The use of demographic variables to understand behavior is another micro level variable that is used to describe differences between adopters and non-adopters (Bradburn & Zimbler, 2002). Also, personality variables, such as self efficacy or innovativeness, are linked to behavioral outcomes (Agarwal & Prasad, 1998; Agarwal, Tanniru, & Wileman, 1997; Burkhardt, 1994).

Informational and Normative Influence

Two predominant micro level variables used to predict behavioral outcomes are attitudes toward performing the behavior and perceptions of what others think about performing the behavior. Attitudes about performing a behavior are comprised of beliefs that are formed by information derived from mass media, independent research, and personal experience. Normative influence is based on information about the set of beliefs and perceptions held by individuals who make up an individual's decision environment. Evidence shows that both contribute to decision outcomes (Ajzen & Fishbein, 1980; Cruz, Henningsen, & Williams, 2000; LaTour & Manrai, 1989; Scott & Scott, 1982; Sheppard et al., 1988; Trafimow & Davis, 1993).

These two sources distinctly contribute to behavioral outcomes. Results from an intricate longitudinal study of innovation adoption reveal that use by visible others changed the perceived utility of a system as well as provided a normative environment for use (Kraut, Rice, Cool, & Fish, 1998). These scholars conclude, "Both routes to the adoption of a new technology coexist and are often reinforcing; both are deeply interwined [*sic*] in organization life, and both can "make or break" the adoption of a new communication system." (p. 451).

The Theory of Reasoned Action

The TRA is a widely accepted and empirically supported model of volitional behavior that suggests behavioral intention is a function of one's attitude and subjective norm (Ajzen & Fishbein, 1980; Fishbein, 1967; Sheppard et al., 1988; Trafimow & Finlay, 2001b). The TRA suggests that attitude and subjective norm are the only determinants of behavioral intentions, and behavioral intentions are proximal to behavioral outcomes. The three variables in the model, behavioral intention, attitude, and subjective norm, are based on individual perceptions that are placed at the micro level of analysis.

Within the TRA, attitude is a variable that represents information about performing a behavior. This variable is defined as the set of outcome-relevant beliefs and evaluations individuals hold about enacting a given behavior. Attitude toward performing a behavior may be strongly positive or strongly negative, and this partially determines whether or not an individual will engage in the behavior. Taking normative influence into account as well strengthens behavioral prediction. This construct is labeled as 'subjective norm', and is conceptualized as actor's perceptions of what important others think about the actor performing or not performing a behavior (Ajzen & Fishbein, 1980). The subjective norm construct also contains information, but this information is based on the preferences of others as opposed to factual or independently derived information about the object of the decision. The TRA purports that attitude and subjective norm are the only direct determinants of behavioral intentions, and that behavioral intentions are proximal to behavioral outcomes.

The TRA recognizes that attitude and subjective norm do not always equally influence behavioral intentions. Prediction of behavioral intention is clear when the contribution of both attitude and subjective norm are equally positive or negative.

However, some behaviors may elicit conflicting values from these two sources, necessitating a measure of the relative contribution of these components. The TRA allows for this differential contribution by accommodating the relative importance each component has on the formation of behavioral intent (Ajzen & Fishbein, 1980).

The contributory influence of attitude and subjective norm is modeled by a regression equation that regresses behavioral intention onto attitude and subjective norm. Consequently, the relative contribution of each behavioral determinant is derived from the regression weight associated with each independent variable; the weights indicate the degree of impact attitude or subjective norm has on behavioral intent. For example, if the weight for attitude is larger than the weight for subjective norm, then one's attitude about performing the behavior will determine behavioral intent.

Ajzen and Fishbein recognized that ideally "the weights of the attitudinal and normative components would be available for each individual with respect to each behavior" (1980, p. 59). However, at the time this theory was proposed, a lack of adequate analysis procedures prevented derivation of individual level weights. Instead, the recommended practice was to capture the relative contribution of attitude and subjective norm with aggregate information.

Recent developments in modeling procedures have made it possible to measure individual variation between these behavioral components (Hedeker et al., 1996). Hedeker and his colleagues derived individual level relative weights to empirically test the idea that the contribution of each component varies across individuals. This assumption was tested with a longitudinal analysis based on multiple observations of behavioral intent, attitude, and subjective norm over time (Hedeker et al., 1996). Their results indicate that variation does exist between the weights for attitude and subjective norm across individuals, supporting this assumption within the TRA. Deriving individual relative weights is a significant contribution to the methods used for testing the TRA because this shift allows for investigation into conditions that may influence the contribution of the behavioral components, presenting an opportunity to further explore and to expand the robustness of this theory.

Micro Level Summary

The most relevant micro level variables to predicting behavioral outcomes are the individually based perceptions of attitude and subjective norm. These two perceptions represent informational and normative influence, which are the two sources of influence commonly recognized throughout the relevant literature. Although it is established that these two factors contribute to behavioral outcomes, and that individual variation in the relative contribution of these weights exists, there remains a question as to which features of a decision context lead to the predominance of attitudinal or normative influence in the formation of behavioral intentions. Macro level propositions also explain individual behavior. In contrast to basing behavior on perceptions individual make about performing a behavior, macro perspectives account for the social context in which a decision is made.

Macro Level Perspectives

Macro level perspectives range from explaining social movements and cultural trends (Strang & Soule, 1998) to describing contexts of individual behavior. Within decision contexts, macro level variables are used to describe how network ties are configured and also to describe network positions that individuals fulfill (Borgatti & Everett, 1990; Erickson, 1988). Both of these properties are expected to influence behavioral outcomes, and both appear at a macro level relative to individual perceptions that appear at micro levels.

One method for modeling macro level effects is through social network analysis, which is designed to model the interaction between contextual properties and individual behavior (Degenne & Forse, 1999). Social network analysis began in the traditions of sociology, social psychology, and anthropology, but its utility has spread to include a much broader range of social scientific disciplines. Social network analysis is seen in multiple theoretical perspectives, such as: Social Cognitive Theory (Bandura, 1986); Structuration Theory (Markus & Robey, 1988; Orlikowski, 1992; Orlikowski, Yates, Okamura, & Fujimoto, 1995); the Theory of Adaptive Structuration (DeSanctis & Poole, 1994; Poole & DeSanctis, 1990); and the Social Influence Theory of Technology Use (Fulk & Boyd, 1991; Fulk, Steinfield, Schmitz, & Power, 1987; Schmitz & Fulk, 1991).

The earliest network analysis was conducted by a sociogram, a measure designed to capture the interpersonal relations among individuals (Moreno, 1953). Sociograms represent individuals by 'nodes' and lines display 'ties' between individuals. Fundamental concepts in network analysis include actors, dyads, triads, and groups, all of which are captured by the ties between individuals. Although the substance of these ties varies, ties typically represent 'advice', 'friendship', and 'adversarial' relations. The analysis of social networks falls into two categories: visualization and algebraic analysis. Both are used to model and explain social contexts (Wasserman & Faust, 1994).

Social network data allow for analysis of different types of network variables. For example, network analysis enables the description of network properties such as size, density, and symmetry. Also, network data allow for describing individuals in terms of network position (e.g., centrality) or network role (e.g., as a 'bridge' between subgroups) (Brass, 1985; Mandel, 1983; Monge & Contractor, 2001; Schmitz & Fulk, 1991). These two functions of social network analysis, the description of network properties through configurations of network ties and the identification of network positions, model micro and macro level variables that are used to describe individual behavior within decision contexts.

Network Tie Configuration

The configuration of network ties influences behavioral outcomes. This macro level includes the whole constellation of social ties that cumulatively describe a decision context. Variables that describe network configuration, such as network density, activity, size, and the degree to which networked individuals possess similar attributes (i.e., network homophily) structure interpersonal influence and behavioral outcomes.

In a study of employee productivity with a new technology, three network-level variables, activity, diversity, and integrativeness, were used to predict behavioral outcomes (Papa, 1990). Network activity was measured by two variables: the size of individual personal networks and interaction frequency. With the goal of capturing personal networks that contained heterogeneous in information sources, diversity was measured by accounting for the number of identified individuals who were situated in different departments and in different hierarchical levels. Integrativeness was measured by the degree of interconnectivity among the individuals selected for membership in the personal networks. Results suggest that network level variables of activity and diversity contribute to employee productivity.

Also, the degree of similarity among network members holds consequences for interpersonal influence. It is expected that individuals will form social ties with similar others, creating a homophilous network where each member has a high degree of common ground with connected others (Brass, 1995; Carley, 1991). In this situation, social influence through these ties is likely because pressure to conform is induced by observing like-minded others. Conversely, heterophilous networks are constructed of connections between dissimilar others. This latter type of interpersonal connection is not as common as the former, as individuals orient toward similar others in general, but when ties occur between dissimilar others the opportunity for novel information flow is possible (Granovetter, 1973).

In addition to the degree of similarity among networked individuals, the pattern of behavior within the network holds consequences for interpersonal influence. For example, critical mass theory focuses the role of the social context in influence processes. Critical mass occurs when behavioral enactment is so widespread within a social network that the pressure created by the social context will encourage the behavior to diffuse to those within the network who have yet to adopt. Hence adoption behavior is influenced by the context of social influence caused by the cumulative adoption of the behavior by others (1990; Markus, 1987).

Generalizing critical mass processes to small group behavior, Valente's (1995; 1996) work on network models the spread of behavioral adoption provides a way to empirically model influence 'thresholds'. The threshold concept is used to describe the tolerance level individuals have before becoming susceptible to normative influence. This threshold model explains individual adoption behavior. Individuals make decisions to adopt based on the proportion of networked others who have already adopted, and the degree of interpersonal influence present within a social network increases as the number of people adopting the behavior. Threshold tolerance is expected to vary per individual and this variance explains why people adopt behavior at different rates.

The strength of social ties is also expected to have consequences for the flow of information and influence. Weak ties can function as bridges between cohesive groups, and these bridges carry information about a diffusing innovation. Although information has been found to flow through these weak ties, strong ties carry influence (Weimann, 1983). Weenig's (1999) study of communication ties and the flow of information and adoption outcomes further illustrates that both attitudinal and normative sources of influence occur within diffusion contexts: awareness of the innovation is related to the number of social ties and attitudes toward the innovation are related to the perceived attitudes of those interconnected by strong ties.

The macro level variables that focus on network tie configuration offer a host of predictors for individual level behavior. These variables include network level measures of density and activity, the degree of homophily among network members, and the role of tie strength. Macro-level predictors also hold consequences for behavioral outcomes and include an individual's position within a social network.

Network Position Variables

In addition to measuring how social ties are configured to describe properties of networks, network analysis allows for the specification and study of network positions that individuals occupy (Mandel, 1983). The derivation of network roles is based on the same information that is used to describe network properties. The difference is that network position variables include individuals rather than the whole network, and just as the configuration of network ties have consequences for individual behavior, network positioning also influences behavioral outcomes.

Measures of centrality represent the degree to which individuals are integrated within a network. A common measure of individual level integration within a network is based on the number of social ties that are assigned to each individual: 'indegree' centrality is based on the number of ties that individuals receive from other members in the network; while 'outdegree' centrality is based on the number of ties individuals give to other members in the network (Freeman, 1979). Another type of centrality is 'betweenness', which represents the number of times an individual falls between two other network members (Bonacich, 1987).

Individuals who occupy the same network position (i.e., structural equivalence) are also relevant to behavioral outcomes. Research indicates that interpersonal influence occurs through direct social ties as well as through the modeling of behavior enacted by individuals who share network positions (Burt, 1980; 1987; 1999). Macro level variables also include: sub-groups of individuals who are bound by cohesive ties (Bovasso, 1996), grouping individuals into 'blocks' identified by shared activity or institutional membership (Anderson & Jay, 1985; Breiger & Pattison, 1986), and modeling interpersonal influences through network segmentation (Baerveldt & Snijders, 1994).

Macro Level Summary

Macro level perspectives offer explanations of human behavior that are based on structural characteristics. Research has shown that interpersonal influence processes are influenced by the macro level variables of network configuration and position. A multilevel perspective offers a mechanism to combine micro and macro level variables, which develops a comprehensive perspective on the role of interpersonal influences on individual behavior. The next section offers a description of multilevel modeling and the propositions enabled by this type of perspective. Then, two multilevel theories are reviewed: diffusion of innovations theory and the structural theory of social influence.

Multilevel Propositions

Multilevel modeling allows for three kinds of propositions. First, inferences can be made about micro-unit variables (e.g., high innovators adopt faster than low innovators). Second, inferences can be made about macro-unit variables (e.g., large organizations have higher absorptive capacity than small organizations). Third, inferences can be made about cross-level effects between micro and macro-units (e.g., in large organizations, high innovators adopt faster than high innovators in small organizations). Figure 1 illustrates a macro-unit proposition, where one macro level variable is specified to influence another variable at the same level. Figure 2 illustrates a micro-unit proposition, where one micro level variable is specified to predict another variable at the same level.

Figures 3a-c illustrate propositions that specify cross-level interactions between macro and micro-units. Figure 3a illustrates a prediction about a macro-unit variable on a micro-unit outcome variable, Figure 3b illustrates a predication about a macro-unit variable on a micro-unit outcome variable while controlling for an additional micro-unit variable, and Figure 3c illustrates a macro-micro proposition where a macro-unit variable is specified to predict the relationship between micro-unit variables. This last instance of a macro-micro proposition represents a cross-level interaction. Models that specify a cross-level interaction term of this type are also known as 'slopes as outcomes' models because the micro-unit variable slopes vary across levels of macro-unit variables (Bryk & Raudenbush, 1992).

The macro-micro relationship modeled by cross-level interactions describes relations between two levels of data. The classification of whether a unit is a macro or a micro variable is based on the nested relationship between variables. A nested variable represents a micro-unit and a nesting variable represents a macro-unit (e.g., in the case of individuals grouped by organization, organizations are the macro-unit and individuals are the micro-unit). In multilevel terms, the presence of one macro-micro relationship consists of two levels: level 1contains the micro-unit variables and level 2 contains the macro-unit variables.

For illustration consider the data on the adoption practices of distance education technology by instructors (Bradburn & Zimbler, 2002). In this dataset, institutions represent the macro-unit and instructors represent the micro-unit. Being multilevel in structure, this dataset allows for the study of institutional effects on instructors, and in particular, the report focuses on how adoption of distance education practice varies by institution type. Distance education adoption represents a micro-unit variable (level 1) and institution represents a macro-unit variable (level 2). Findings indicate that, at the micro level, females are more likely to use distance education technology in comparison to males. At the macro level, instructors employed by public two-year institutions are more likely to engage in distance education in comparison to private not-for-profit doctoral or liberal arts institutions (Bradburn & Zimbler, 2002).

A study of the contributory role of attitude and social norm toward smoking behavior (Hedeker et al., 1996) presents another example of a multilevel data structure. Micro-unit variables were constructed of multiple measurements of attitude and subjective norm. Sex, specified as a macro-unit variable, was added to the model to investigate the relative weights of attitude and subjective norm. In this example, observations are level 1 variables and sex is a level 2 variable. Their findings suggest that the influence of subjective norm on behavioral intent was determined, to some extent, by an individual's sex, with females being more likely to base their intentions on their normative environment than males.

Multilevel modeling is not limited to specifying a single macro-micro relation between levels of data; it has the capacity to accommodate more than one macro-micro relation. The presence of two macro-micro relations creates a three-level model. For example, if one were to add students to the data on the national survey of faculty, a three level model would be created where students (level 1) are nested within instructors (level 2) who are nested within institutions (level 3). A macro-micro proposition could be based on the variables present in levels 1 and 2; students are the micro-units and instructors are the macro-units. If this dataset included variables related to the student unit at the first level, the data could be analyzed for instructor effects on student level variables (e.g., instructor teaching style on student satisfaction or performance).

Multilevel Perspectives

Diffusion of Innovations Theory

The spread of ideas, information, and behavior has been the focus of study for behavioral scientists within many disciplines, producing an extensive body of literature (Burt & Janicik, 1996; Lynch, 1996; Rogers, 1995; Valente, 1995). Developed over the past three decades, diffusion of innovations theory provides a comprehensive treatment of the diffusion effect by introducing explanatory variables of individual behavior within diffusion contexts (Rogers, 1995). The aim of diffusion research is to explain and predict adoption of innovation. This theory also prescribes procedures that can positively impact diffusion rates, which is useful for practitioners interested in strategically planning for the spread of a new innovation (Rogers, 1995). This theory is multilevel in that it accommodates both macro and micro level variables by predicting diffusion outcomes based on individual and structural characteristics of the diffusion context. Macro level variables include properties of the diffusion context and an individuals network position and micro level variables include innovation-related perceptions. Four elements are included in this theory: properties of the diffusing innovation, communication channels, time, and the social system in which diffusion occurs.

Innovation

Innovations are defined as any new idea, practice, or technology that has the opportunity to spread across a diffusion context. Regardless of how long an idea, belief, or behavior has been in existence, an innovation is defined as an idea, belief, or behavior that is perceived to be new to an individual or group of individuals. Hence, 'innovation' is a generic term used to describe anything that is new to potential adopters.

The type of innovations included in diffusion research spans a broad range of behaviors and ideas, or "From Hybrid Corn to Poison Pills" (Strang & Soule, 1998). Innovations studied have explained adoption of a new medical drug (Coleman, Katz, & Menzel, 1966); purchasing new products (Summers & King, 1969); using a new computer mediation lab, adopting personal computers, and using a certain web page (Dutton, Rogers, & Jun, 1987; Katz-Jameson, 1998; Weare, Musso, & Hale, 1999); and promoting HIV prevention behaviors (Kelly et al., 1991). Diffusion research is also aimed toward understanding why innovations fail to diffuse (Riemer-Reiss, 1999).

Five innovation characteristics are identified which influence the time it takes for an innovation to diffuse. Innovations are expected to diffuse more rapidly if (1) they possess a relative advantage over existing practice, (2) they are compatible with values and norms held by potential adopters, (3) they are easy to understand, (4) they can be tried-on for size before final commitment to adoption, and (5) the innovation is visible to others (Rogers, 1995).

Communication Channels

Communication channels allow for the flow of information. Two types of communication channels are distinguished: one describes information generated from a mass media source ('one-to-many'), and the other describes the exchange of information among individuals ('one-to-one'). Each type is considered an information source and each play a role in a "two-step" flow model of influence (Katz & Lazarsfeld, 1955). The first source represents the flow of information from public means and the second source represents information flow among interconnected individuals. Diffusion is possible by the second step because it enables the spread of information derived from mass media sources.

Communication channels are essential to diffusion processes because they serve as the conduit for innovation-related information as well as interpersonal influence. These channels make up the fundamental process through which diffusion outcomes occur: information enters a social system, it flows through a structure of social ties, and it impacts individual cognitive processes that lead to adoption decisions.

Time

There are two senses of time in the diffusion process. The first occurs at the individual level. This process begins with the acquisition of knowledge and proceeds to the development of an attitude toward the adoptive behavior concluding with the actual decision about whether to adopt the behavior (Rogers, 1995). Progress through these states takes time, and individuals vary in the rate of their adoption (or non-adoption) decisions.

Individuals vary in the time they take to adopt an innovation, and adopter categories are used to describe adopters who adopt in non-uniform patterns within a diffusion context (Degenne & Forse, 1999; Valente, 1996). Rogers classifies individuals into the following categories: innovators, early adopters, early majority, late majority, and laggards. Innovators are the first to adopt an innovation. These individuals typically hold higher socioeconomic status in relation to other individuals with in the diffusion context, they possess personality characteristics that are amenable to change, and they engage in more extensive communication behavior within and beyond the diffusion context. Innovators influence individuals with whom they are connected, and those who are influenced are labeled 'early adopters'. The early adopters possess influence power over other members within the diffusion context, and the individuals they influence are labeled the 'early majority'. Although susceptible to influence by the early adopters, the early majority influences individuals in the 'late majority', and the late majority individuals influence the 'laggards'.

Second, at the contextual level, time is factored into the diffusion process to describe the rate of adoption within a diffusion domain. In contrast to the amount of time it takes for an individual to process social and innovation-related information, adoption rate focuses on the relative speed within which an innovation spreads across a diffusion context. A well-supported phenomenon of the diffusion process is the "S" curve that adoption patterns form. The proportion of individuals who adopt changes over time, beginning with innovators, who are few in number, leading to adoption by the majority and eventually reaching the laggards (Rogers, 1995).

Social Systems

The structure of the diffusion context also influences adoption outcomes. Diffusion contexts are systems that exist as long as individuals within the system are bound together on relevant dimensions. Individuals are embedded in these bounded social systems and they are connected to each other through communication ties. These ties shape and are shaped by the larger social context. The role social systems play in diffusion processes is best described through a network perspective. Diffusion theory allows for the inclusion of macro level variables in terms of network position (i.e., opinion leadership) and network configuration (i.e., homophily), and research indicates that both types of network variables help to explain diffusion outcomes.

Individuals who are central within a diffusion network play a key role in diffusion processes. These individuals are labeled 'opinion leaders' and possess certain properties that make them influential over networked others. For instance, opinion leaders hold strong, well-defined opinions about an innovation, they have access to relatively more external communication, they are accessible to others, they hold a relatively higher socioeconomic status, and they have a high number of communication ties relative to other individuals within the social system (Rogers, 1995). Although influential, few opinion leaders are expected within any diffusion network. Evidence shows that opinion leaders exert influence over other members of diffusion context and that targeting opinion leaders is an effective way to accelerate diffusion rates (Kelly et al., 1991; Rogers, 1995; Summers & King, 1969; Valente & Davis, 1999).

Opinion leaders are identified through reports of who is likely to be influential, self-identification, and observations of a diffusion context (Rogers, 1995). Assessing the pattern of communication ties within the diffusion context also identifies opinion leaders. The analysis of communication networks provide information about the relative number of ties individuals give and receive, and opinion leaders are identified by their relatively high number of ties (Rogers, 1995). Consequently, opinion leadership is measured by an individual's position within a network of communication ties.

Network configuration also impacts the influencing force of opinion leadership. Opinion leadership is most influential within radial network configurations, which are defined as networks in which one individual is connected to many. Radial networks are the optimal configuration for diffusion outcomes via opinion leadership because the central person is the only source of information and interpersonal influence. In contrast, networks that consist of individuals who are connected to everyone else, labeled as interlocked networks, reduce the influential potential of the opinion leader. In interlocked networks, multiple sources for information and influence exist (Rogers, 1995). Another network level property that is expected to influence diffusion processes is the degree of homogeneity within networks. Networks constructed of homophilous individuals will experience a slower rate of adoption behavior in contrast to heterophilous networks (Rogers, 1995).

The future of diffusion research lies in the concurrent analysis of micro and macro variables (Rice & Gattiker, 2001). The answer for which source of influence, attitudinal or normative, prevails over behavioral decisions may lie in a multilevel perspective. Developing an understanding of the conditions that shape the relative contribution of attitudinal or normative influence will extend the predictive and practical power of this theory. The beginnings of such an understanding is offered by the structural theory of social influence.

The Structural Theory of Social Influence

As a multilevel theory, the structural theory of social influence (SSI) accounts for micro and macro level variables in the prediction of individual behavior (Friedkin, 1998). This theory situates behavioral decisions (micro level) within a decision context (macro level) that is described by network information. Similar to other work on predicting behavior as a function of interpersonal influence, Friedkin emphasizes the import of modeling influence both at the individual and at the structural level (1998):

> A structural social psychology begins with the understanding that an episode of interpersonal influence is not an isolated event, but one that occurs among many other interpersonal influences. In the context of such a system of interpersonal effects, one cannot understand how actors come to hold particular opinions or behave in particular ways without taking the system of effects into account. (p. 34)

The SSI contains components of both the TRA and diffusion of innovations theory. In parallel with the TRA, the SSI specifies two behavioral determinants at the micro level: attitude and normative influence. Individual attitude is a product of beliefs and information about performing a behavior and normative influence is defined as "the influence of the collective other on the individual" (Friedkin, 1998). Individual attitudes are formed by exogenous influences that lie outside of a social network, and normative influence is endogenous to a social network. Similar to diffusion of innovations theory, the SSI is a multilevel theory of behavioral choice, which situates individual level decisions as they occur within a context of social ties. The SSI is distinguished from the TRA and diffusion of innovations theory in that it offers an explanation of how individuals come to behavioral decisions within diffusion contexts. In particular, one component of the theory stipulates that network centrality predicts the relative contribution of attitude in the formation of behavioral intent.

The overall purpose of the SSI is to model a system of interpersonal influence, one that consists of interpersonal connections at the individual level and 'ridge structures' at a structural level. Ridge structures are made up of cohesive individuals who occupy "sequentially overlapping and densely occupied regions of social space" (Friedkin, 1998). And they describe a "sufficiently well-connected social structure that such linkages within and between subgroups are dense enough to permit mutual influence processes to equilibrate toward uniformity" (Strang, 2000). The production of a ridge structure is based on three theoretical pillars: the probability of interpersonal attachment, the relationship between self and other, and the implications of social position.

Probability of Interpersonal Attachment.

The first pillar of the SSI encapsulates the idea that interpersonal influence occurs through a network of interpersonal attachments that enable the flow of information and ideas among linked individuals. Because influence occurs through these social ties, it is assumed that the likelihood of an interpersonal tie between individuals will lead to a greater likelihood that one of these actors will exert some influence over another.

This probability is estimated by identifying multiple types of network properties that contribute to the likelihood of an interpersonal tie. These nine properties are: (1) the outdegree of actor *j*, or the number of ties *j* sends; (2) the indegree of actor *j*, or the number of ties *j* receives; (3) the number of occurrences of a tie from actor *j* to actor *k*; (4) the number of actors who send ties to *j* and *k*; (5) the number of actors to whom *j* and *k* both send ties; (6) the number of actors to whom *j* sends a tie and from whom *k* receives a tie; (7) the number of actors from whom *j* receives a tie and to whom *k* sends a tie; (8) the outdegree of actor *k*, or the number of ties *k* sends; (9) and the indegree of actor *k*, or the number of ties *k* receives (Friedkin, 1998). As independent variables, each network property is used to predict the likelihood of an interpersonal tie. It is proposed that these variables describe the immediate network environment surrounding the two individuals. In this immediate network, individuals have access to information and the ability to influence each other.

The focus of this pillar is not on the actual attachment that exists between two individuals, but on the probability of such an attachment. The theoretical basis and import of this pillar is that it integrates traditions in structural analysis that afford predictions of interpersonal influence outcomes. Specifically, an interpersonal connection is likely to occur when certain structural conditions are met, and the SSI predicts this likelihood through the formation of ridge structures (Friedkin, 1998). Ridge structures are formed as the probability of interpersonal attachment increases, which occurs when members within a network are relatively proximal to one another. Proximity is related to cohesiveness, and cohesiveness among individuals produces a ridge structure. Hence, a ridge structure is expected to occur in a network of individuals who have a high probability of an interpersonal attachment with like-positioned others.

The Relationship Between Self and Other

The second theoretical pillar of the SSI suggests that individuals assign differential weights to attitudinal ("self") and normative ("other") influence. The weighting distribution is a function of structural position. In particular, central individuals are expected to place a heavy weight on their attitude in relation to individuals who occupy peripheral positions within a network. The weights between self and other reflect an inverse relationship; a heavy weight on one component necessitates a light weight on the other.

The 'coefficient of social influence' describes this self-other balance: The weight for other is theorized to be dependent on the weight for self; the weight for self is theorized to be dependent on structural centrality. In contrast to the TRA, which empirically estimates the relative weights of attitudinal and normative influence, the SSI bases the self-other balance on network position. Structural centrality is the basis for calculating the relative weights; self-weight is determined by structural centrality, and other-weight is derived from the self-weight.

By introducing a macro level predictor of the relative weights between attitude and normative influence, this stipulation is a contribution to the prediction of interpersonal influence because it proposes one explanation for how these weights are distributed across individuals. The theoretical basis for this assumption is that central individuals hold a position of power within a network, an idea supported by the work of Brass and Burkhardt (1993). Central individuals are in a position of power because they have more control over the flow of information. Consequently, individuals in a central position within a network are expected to hold a broad scope of influence across many network members.

Friedkin offers support for the assumed relationship between self and other by describing the relationship between this balance and the probability of an interpersonal attachment, the concept detailed within the first theoretical pillar of the SSI. He asks us to consider two actors, *j* and *k*. The probability of an attachment between these two actors is positively associated with the indegree of actor *k* and this probability is negatively associated with the indegree of actor *j*. In other words, individuals are more likely to orient toward a central network member rather than one who occupies a peripheral position, and an individual who occupies a central position is less likely to orient toward another individual who is central than toward an individual who occupies a peripheral network position. "This latter finding suggests that a central actor is more self-absorbed than a peripheral actor and is consistent with the thesis that an actor's self-confidence, self-respect, and resistance to opinion change are functions of the actor's power basis" (Friedkin, 1998).

In sum, the SSI stipulates that central actors are less susceptible to normative influence in comparison to individuals in peripheral network positions. The implication for this assumption is that "high self-weight precludes a flow of influence to the actor; hence, a heavily self-weighted actor (a heavyweight) can be only a source of influence" (p. 203). In terms of diffusion of innovations theory, heavyweights are analogous to opinion leaders because heavyweights and opinion leaders possess influencing power over others.

The degree to which individuals are integrated within a network is assessed by a measure of structural centrality. Within the SSI, the calculation of structural centrality is not solely based on the number of indegree ties received by individuals. In addition to accounting for indegree scores, the calculation of structural centrality accounts for the average indegree of a whole network. This average is a network level property that is commonly described as 'density'. A network density score is relative: a high score represents a network in which many network members have social ties to each other and a low score indicates a network whose members are sparsely connected.

Dense networks, calculated by dividing the sum of all network ties by the total possible ties (Wasserman & Faust, 1994), are theorized to suppress the relationship between self weight and structural position. Factoring in the average network density in the calculation of indegree "dampens the centrality of actors in networks where the probability of an interpersonal tie is high" (p. 93). The balance between self and other as a function of structural centrality is expected in networks that have relatively low density. Consequently, self-weight and network density are related in that "an increase in the density of interpersonal ties (mean indegree) lowers self-weight" (Friedkin, 1998, p. 96).

The equilibrium relationship between structural position and individual attitude weight is illustrated within Table 1, which represents output generated by the formula used to calculate attitude weight as a function of structural position (Friedkin, 1998). The table illustrates that as mean indegree increases, the number of individual indegree scores required to tip the balance toward a heavy attitude-weight (one that exceeds .5) increases. As mean indegree decreases, the number of individual indegree scores required to tip the weighting balance toward a heavy attitude-weight decreases.

As the mean indegree scores reach a certain threshold, the table illustrates that no number of individual indegree ties will tip the balance toward self-weight. Consequently, normative influence will contribute more toward the decision outcome when the mean indegree suppresses attitude-weight. This table also illustrates that regardless of network density, self-weights for central positions are always heavier than self-weights for peripheral positions.

High-density networks are one of the three components required to create ridge structures. Ridge structures emerge from cohesive environments with a high probability of interpersonal attachments among similarly positioned network members. In ridge structures, it is expected that average indegree scores among individuals are high, resulting in low self-weights and high other-weights for all network members. This creates a decision environment where normative influences are theorized to play a larger role than individual attitude. As Friedkin states (1998):

> In a network where all actors have noteworthy bases of power and high indegrees, centralization is not as meaningful as in a network where power bases are concentrated in a subset of actors. The structural situation of the group is more consistent with that of a 'company of equals' than with that of a group in which there is marked stratification of interpersonal influences. (p. 96)

Individual Level Variables

The SSI does not propose a direct measure of weights for attitudinal or normative weights. Instead, attitude weightings are derived from a formula that is based on network position, reflecting the assumption that attitudes are connected to centrality. Friedkin (1998) suggests the following formula, where w_{ii} = individual attitude weight and c_i = centrality (p. 57):

$$w_{ii} = 1 - \sqrt{(1 - c_i)}$$

Similarly, the weight for normative influence is derived from the attitude weight, which is based on the assumption that attitude and subjective norm represent 'two sides of the same coin'. Weightings of individual attitude and normative influence are related as follows:

$$w_{ii} = 1 - a_{ii}$$

Centrality scores are the heart of both attitudinal and normative influence (p. 98):

$$\begin{aligned} \sqrt{(1 - c_i)} &= a_{ii} \\ &= 1 - w_{ii} \end{aligned}$$

The Implications of Social Position

The third theoretical pillar of the SSI describes the implications associated with holding a particular social network position. In particular, networked individuals who occupy the same structural positions will come to possess converging attitudes and behavioral orientations, as described by Friedkin (1998):

> The joint occupants of a social position are subject to the same set of conditions (including influential opinions), and they are affected by these conditions and opinions in an identical way; the immediate implications are (a) that the joint occupants of a social position have identical initial opinions on issues and (b) that the expected differences of initial opinion among actors (which correspond to the distances between their social positions) are obtainable from an analysis of the actors' profile similarities in the influence network. (pp. 110-101)

Similarity in structural positioning is estimated by two properties: calculating the social distance between network members and computing the extent to which network members share the same structural positions (structural equivalence). It has been found that individuals who occupy similar network positions will also share the same set of attitudes, opinions, and behaviors. An example of this outcome is seen in the relationship between structurally equivalent individuals and the similarity in behavioral enactment (Burt, 1987; 1996). As position similarity leads to similar attitudes, position dissimilarity leads to differences between initial attitudes due to social distance between network members. This third pillar holds theoretical import because it enables the prediction of clusters of common initial attitudes, which further contributes to the formation of a ridge structure.

SSI Summary

Five analytical steps are involved with testing the SSI. The first step requires the definition of a network of interpersonal ties. The second step requires social network analysis procedures to produce centrality scores for each network member. Centrality scores are based on the indegree of each actor. The probabilities of interpersonal attachments are calculated in the third step with a logistic regression that specifies structural properties to predict interpersonal connections. The fourth and fifth steps involve additional network analyses to derive network position dissimilarity and equilibrium, as captured over time.

The three pillars of the SSI are each represented within these five steps. Step one provides data that are used within the first and second pillars, which are satisfied by calculations conducted in steps two and three. Steps four and five yield information that applies to the third pillar. Although each pillar contains assumptions that are subject to empirical investigation and support, the assumption within the second pillar, the stipulation of the self-other balance as a function of structural centrality, is of particular interest in this investigation.

Study Rationale

The SSI accommodates a multilevel perspective by situating interpersonal influence processes within a social context (2001; Friedkin & Johnsen, 1997; Friedkin, 1998). This theory has the potential to contribute to our understanding of interpersonal influence in light of macro level effects. In particular, an assumption within the SSI suggests that a structural predictor explains the relative contribution of informational and normative influence in the formation of behavioral intent. A test of this assumption will provide information about the conditions that impact the contributory influence of attitudinal and normative influence.

Although the SSI is considered a "powerful approach to social influence processes" (Strang, 2000), the assumption underlying the second theoretical pillar requires empirical support. Doubt is cast onto this assumption through exploring another interpretation of the connection between structural centrality and influence outcomes. In contrast to the SSI's assumptions that network centrality presents opportunities for increased power and a broad influence base, an equally plausible interpretation is that increased contacts lead to greater influence due to an increase in the amount of normative information available. For those with high centrality scores, the pool of normative influence sources is larger than for individuals who are peripheral to a network. This also extends beyond direct ties to include secondary ties; the likelihood that one will be exposed to multiple sources of attitudes and behaviors is much higher for central people. Given this, an alternative hypothesis could be that individuals who are centrally positioned within a network may have more pressure to comply with normative influence, and individuals in peripheral structural positions may feel less cumulative pressure from these influences due to the fewer number of people available to exert interpersonal influence (Durrington, Repman, & Valente, 2000; Valente, 1995).

The role of structural positioning in predicting the relative contribution of informational versus normative influence is worthy of study. This study tests one predictor of these relative weights. In doing so, this study tests one assumption within the SSI. Support of this assumption is critical to the theory, as this pillar supports the higher-level predictions of attitudinal convergence across networks over time, a phenomenon predicted within the third theoretical pillar.

Hypothesis

The purpose of this investigation was to provide an empirical test of the theoretical assumption within the second theoretical pillar of the SSI. The following hypothesis was derived from the assumed relationship between attitude weight and centrality, described as follows (Friedkin, 1998):

> A central actor is less susceptible to interpersonal influence than a peripheral actor, and a manifestation of this relationship is a decline in the probability of an actor's orientation toward others with an increase in others' orientations toward the actor. Thus, structurally central actors are heavyweights and peripheral actors are lightweights with respect to the weights that they allocate to their own opinions. (p. 88)

The relationship between these variables is the degree to which each impacts the way behavioral intentions are formed as a function of structural position. Friedkin assumes that attitude exerts more influence on behavioral intention for central actors than for peripheral actors. Hence:

Hypothesis: As structural centrality increases, the weights associated with attitude will increase.

Research Question #1

In the search for variables that can predict the relative contribution of attitude and normative weights, one possible complication is that the relative weights may vary by behavior. Although the SSI predicts variation of these weights across structural position, it is also reasonable to expect variation of these weights across behavioral issues. This orientation would suggest that weights are assigned depending on the nature of the information available regarding the behavioral issue in contrast to one's network position.

There is evidence that suggests a relationship between the relative weights of attitudinal and normative influence and behavior type. Research shows differences in the contributory influence of attitude and subjective norm with judgmental or factual decision tasks. For judgmental tasks, individuals will orient toward their normative group when making a decision, but for factual decisions, one's own opinion takes precedence (Trafimow & Davis, 1993).

The weighting distribution is also influenced by the amount of information available from each influence source (Eagly & Chaiken, 1993). For instance, according to the Heuristic Systematic Model (HSM), if a decision environment contains enough normative clues (termed 'heuristics' within the theory) to aid in drawing a conclusion, more weight will be placed on this component in comparison to the attitudinal component. However, if the normative clues fail the sufficiency test, then more information will be sought to draw a conclusion. These examples illustrate that behavioral aspects may also play a role in how attitudes and normative influences are weighted. This point is not overlooked by Friedkin (1998):

> Self-weight may be diminished by a demand for consensus on issues and by societal traditions that value deference and compromise over debate and conflict. Moreover, within a common set of contextual conditions, the balance between self and other may vary for different types of issues. In short, there is plenty of scope in the proposed framework for an elaborated special theory of the self-other balance. My approach, which links the self-other balance to the centrality of an actor in the network of interpersonal attachments and to the status-organizing processes that have shaped this network, is a starting point for such a theory. (p. 98)

Although there is reason to believe that behaviors can influence the relative weight of attitude and subjective norm, the SSI does not explain this source of variation. This issue is worth exploring based on what is known in other research areas about decision-making processes across different decision types. Hence:

> RQ1: Do the weights associated with attitude and normative influence vary according to behavioral issue?

Research Question #2

The measurement of relative weights between attitude and subjective norm is another area worth exploring in this study. A direct measure would improve TRA methodology because weights for each individual can replace the estimated weights currently suggested by the model. Ajzen and Fishbein suggest that individuals may not be capable of providing these weights (Ajzen & Fishbein, 1980). However, the HSM justifies an attempt to capture weights via a self-report measure (Eagly & Chaiken, 1993). As an exploratory exercise, this study included a single-item self-report measure of relative weights to compare this data to the empirically derived weights. The second research question will investigate this comparison:

> RQ2: How does a self-report measure of relative weights between attitude and normative influences compare to empirical weights?

CHAPTER 3: THE TEST OF A STRUCTURAL PREDICTOR

The multilevel model in this study included individual perceptions about performing teaching behaviors at a micro level and social network position at a macro level. Individual perceptions toward teaching behaviors were operationalized following the methods proposed within the TRA, which indicates that attitude and subjective norm are the two most important perceptions in forming behavioral intentions. To test the hypothesis, multiple observations were required at the micro level to derive the individual relative weights between attitude and subjective norm. Furthermore, social network data were required to derive centrality scores for each individual within a social network.

Participants

Participants included University of Arizona employees who held Full, Associate, Assistant, and Adjunct Professor teaching positions during the Fall 2001 term. The pool of participants was further limited to include only those employees who intended to teach during the Spring 2002 term. Only teaching faculty were included because the behavioral focus was teaching, and this behavior domain is directly relevant to those who anticipated teaching a course in Spring 2002. Participants were grouped according to departmental membership and descriptive information included disciplinary membership as well as academic rank. Overall, 39 full professors, 27 associate professors, 26 assistant professors, and 23 adjunct or visiting professors completed the survey instrument. Table 2 contains respondent information for each department and Appendix A contains the list of behaviors included in the study.

Measures

The survey measures include: (1) a social network measure for each department to enable calculation of individual structural centrality; (2) attitude measures for each of seven teaching behaviors from each participant; (3) measures of others' attitudes toward enacting each of seven behaviors; (4) measures of motivation to comply with each individual identified, and (5) a self-reported measure of relative weights between attitude and normative influence for each behavior. Each measure is reviewed in this section.

Structural Centrality

Social network analysis concurrently models the relationship between micro and macro level variables and enables cross-level analyses (Lawler, Ridgeway, & Markovsky, 1993; Price et al., 1991). A social network measure was necessary to collect the data required to compute structural centrality scores for each individual. Academic departments defined the network boundary, and each department was treated as one whole network. For each department selected, the network measure contained a list of all faculty members within that department.

Social ties among faculty members within each department were operationalized along two dimensions: direct communication and behavioral visibility. The influential force of social ties can occur either through direct communication channels or through the visibility of networked individuals who have higher profiles in comparison to others within the network. According to Friedkin (1998), 'visibility' occurs when one's attitudes and behavior are visible, or accessible, to others, and this outcome is possible through issue-related interaction or through 'supplemental' visibility. An issue-related interaction tie between individuals represents direct communication with another and supplemental visibility is described as gaining knowledge of attitudinal dispositions through indirect means; either by overhearing, attending a presentation, or by gaining information from secondary links (i.e., a friend of a friend or through peer review based on annual performance reports). Both of these sources, interaction ties and supplemental visibility, are expected to carry attitudinal and behavioral information.

The direct communication link was operationalized by asking with whom an individual interacts on the issue of teaching. The indirect behavioral visibility link was operationalized by asking with whom an individual has general knowledge of the behavior enacted by networked others. Both of these dimensions were used to represent a social tie, and the social network for each department was based on the presence of both types of ties. The wording of this measure was as follows:

> This measure contains a list of your fellow department members. Scan the list, and place a check by the names of the people with whom you have:
>
> (1a) had discussions with on the topics of teaching.
>
> *and* /or
>
> (1b) some knowledge about the teaching behaviors this person enacts, either through directly witnessing such behavior or by secondary means, such as hearing about one's teaching practices from a second party.

These data yielded network information from which the structural position of centrality was calculated for each network member. Structural centrality scores were based on the number of social ties received from networked others while factoring in the overall density of the network (Friedkin, 1998). Indegree scores for each network member were computed by accounting for the relative indegree scores within the whole network so that networks with generally high average indegree scores suppressed the value of a single network member.

Although it is desirable to have complete network data to compute any network position variable, recent study has indicated that measures of indegree centrality are robust to incomplete network data. With the use of a bootstrapping technique, Costenbader and Valente (2002) found that indegree centrality calculations maintain fairly high correlations between sampled and actual data. For instance, a 50% sample reflects correlations that range from .85 to 1.0, a 40% sample reflects correlations that range from .78-.92, and for a 30% sample correlations range from .74 to .91.

In the interest of obtaining the most reliable centrality scores, the networks included in the data analysis for this study were limited to those with the highest response rates. To maximize the number of respondents included in the data analysis and to ensure that the indegree measure of centrality was valid, a cut-off point for response rates was set to 30%. This cut-off criterion struck a balance between removing departments from the dataset and retaining the largest number of individual responses (i.e., removal of one department resulted in the removal of up to 10 participants). Response rates for the initially surveyed 20 departments ranged from 13% to 65%, and the seven departments whose response rates were below 30% were removed. Table 4 also contains information about the number of instructors who completed the network measure for each department along with response rates for each department. It is relevant to note that the response rates used to select departments to include in the final analysis were based only on responses to the network measure. For the respondents who intended to teach during the Spring 2002 term, which satisfied the 'time' requirement within the TRA model. Table 5 illustrates the difference in response rates between those who completed the network measure (presented first in the survey) and for those who completed the entire survey.

Attitude

A direct measure of attitude was required to test the assumption that the contributory weight for attitude is predicted by one's position of structural centrality. The TRA contains operationalizations of attitude and subjective norm, and this theory is closely aligned with the individual-level assumptions of the SSI. Ajzen and Fishbein recommend two methods for measuring this construct. One is to measure beliefs and evaluations for each behavior to capture a detailed summation of each belief and respective evaluations. The other method is to conduct a general evaluation of attitude. The latter method was used in this study to captures one's positive or negative orientation toward performing a behavior. The general (summative) measure was preferred over the belief/evaluation method because it better controlled the length of the questionnaire. Ajzen and Fishbein (1980) approve of this use of the general measure, pointing out that "it is not always necessary to measure all of these [the model's] variables to answer certain questions" (p. 98).

Behavioral prediction is improved when measures of behavioral intentions, attitude, and subjective norm are phrased to include the dimensions of action, target, context, and time. For instance, measurement items should be worded to include all four of these dimensions, like so, 'Use of the Web (action) by instructors (target) to present course content in class (context) during the Spring 2002 semester (time)'. The behaviors in this study were measured along these dimensions (Ajzen & Fishbein, 1980). The attitude construct was measured by three seven-point Likert-type items that were designed to tap into a general behavioral evaluation. Scores for this measure ranged from –3 (strongly negative evaluation) to +3 (strongly positive evaluation). Appendix B contains the attitude measure.

Subjective Norm

In addition to providing a measure for the attitude component, the TRA offers a measure of normative influence designed to capture one's subjective perceptions of the opinions held by networked others. This measure captures perceptions of what others think about the perceiver performing a particular behavior (i.e., 'I think that person A thinks that I should/should not enact this behavior'). These perceptions are combined with a measure of the extent to which an individual was motivated to comply with each identified other, and subjective norm is a result of the summed product of perceived other's attitude and motivation to comply.

The subjective norm measure as proposed by the TRA was altered to more closely represent the conceptualization of normative influence within the SSI. According to the SSI assumptions, interpersonal influence is due to the visibility of others' attitudes and behaviors; hence a measure of this construct would reflect this expectation by including observed behavior and others' attitudes toward enacting the behavior. Instead of measuring what others think one should or should not do, the measure used in this study captured a normative environment that was made up of perceived behavioral enactment and corresponding attitudes of identified others. This shift in measurement is also aligned with Bandura's notion that influence occurs through modeling of others behavior and attitude (Bandura, 1986).

The normative measure used in this study focused on the perception of what attitudes were held by important others in regards to how they felt about performing the behavior. For example, if person X chose person Y as an important other, person X was asked to report their perceived attitudes of what person Y thinks about performing the behavior. Perceived attitudes were measured by asking individuals for their best guess about the evaluation each identified other had toward the enactment of each of seven behaviors. In the interest of survey brevity, a one-item seven-point Likert-style measurement item measure was used. The following question was asked for each important other identified, "I think that [person 1…n] thinks that performing [behavior 1-7] is: Favorable/unfavorable". Scores for this measure ranged from 1 (unfavorable) to 7 (favorable). Motivation to comply with each identified other was assessed by one seven-point Likert-type scale, which read as: "In regards to teaching practices in general, I want to do as [person 1…n] does". Scores for the motivation to comply measure ranged from 1 (strongly disagree) to 7 (strongly agree). Appendix C contains the measure of other's attitude, and Appendix D contains the motivation to comply measure.

Behavioral Intentions

The TRA offers a method to derive relative weights for the contributory impact attitude and subjective norm have toward the formation of behavioral intention. This model provides a mechanism to empirically calculate these values. A regression model is specified that regresses behavioral intent onto attitude and subjective norm, and the regression weights for attitude and subjective norm represent the relative contribution each component has on behavioral intentions. Therefore, a measure of behavioral intentions was included to complete the TRA model. The measure of behavioral intent was phrased to include the recommended properties of action, target, context, and time (Ajzen & Fishbein, 1980). For example, the behavior of using a course listserv was phrased as: 'I intend to use a listserv in teaching my class(es) for the Spring 2002 term'. Intentions to perform each behavior were recorded on one seven-point Likert-type scale that ranged from 1 (extremely agree) to 7 (extremely disagree). Appendix E contains the behavioral intent measure.

Self-Reported Relative Weights

A measure of self-reported weights was included to address research question #2, which inquired about how self-report weightings compare to empirically estimated weights. This measure was designed to capture the degree to which one component received the heavier weight, and it asked respondents to rate how much confidence he or she has about basing a behavioral decision on a) 'my own attitude' or b) 'what others think/do'. This was a one item seven-point Likert-type scale that ranged from 1 (my own attitude) to 7 (what others think/do).

Measurement Order

Presentation order for the measures of attitude, subjective norm, and behavioral intentions were varied for each participant to mitigate any possible measurement effects of self-generated validity (Davis & Venkatesh, 1996; Feldman & Lynch, 1988). The 'self-generated validity effect' describes a measurement artifact in which prior responses influence subsequent responses; it is an effect of particular concern to research that includes questionnaires in a path-model design. TRA models are subject to this effect because the constructs of attitude and subjective norm precede behavioral intentions, and presenting measures in this order may influence the correlations between the model components beyond what the theory predicts. All measures were presented in various orders for each respondent with the exception of the social network measure. This measure was presented first for all respondents, as the individuals identified in this measure were used in the subsequent measures.

Procedure

The study employed a cross-sectional design that captured network configuration and individual level perceptions of attitude and subjective norm as they appeared at one measurement occasion (Cook & Campbell, 1979). This design is sufficient to test the theoretical assumption within the SSI because the assumption is not time dependent; individuals in central positions are assumed to always weigh their attitude heavier than subjective norm.

Department Selection

Department selection was based on departmental size, measured by the total number of Full, Associate, Assistant, and Adjunct instructors within departmental boundaries, and estimated willingness to participate. Both selection criterions have consequences for the quality of data collected. For departmental size, it was important to select departments with a minimum size because departments that have too few instructors may not reveal a satisfactory range in structural positioning (i.e., they may be more integrated as opposed to radial in structure), and departments with too many instructors may contribute to respondent fatigue and adversely influence the survey data.

As department size increases, the structural landscape is more likely to reveal a central-peripheral structure, which reflects variation in centrality scores. Faculty in small departments are more likely to interact with every other departmental member, creating a context in which there is little variation in centrality scores due to a highly integrated social context. Consequently, the minimum departmental size was set to 20 because it is assumed that networks smaller than this will often share the same 'horizon of observability'. In these cases, it is likely that each network member is visible, and presumably connected, to every other network member (personal communication, Valdis Krebs, July 26, 2001).

Setting the minimum network size was in response to concerns about obtaining variation in network positions. It was also relevant to consider the maximum network size due to concerns about respondent fatigue. Respondent fatigue is an important consideration with network data collection because accuracy may be compromised if respondents are asked to identify social relations with many others. This problem is compounded when the size of personal networks is quite large and when additional data is required, as was the case with the survey used in this study. The questionnaire was designed to not only capture social ties, following a traditional social network analysis, but to also study individual level perceptions of attitudes and norms, following standard practice in attitude measurement.

Setting a maximum size for network inclusion is difficult to do *a priori* because there is little guidance by way of anticipating fatigue effects. Experts in the field of network analysis were consulted, and they agreed that there is little concern that networks in excess of 120 individuals will compromise network data. In light of this consultation, no maximum network size was specified because the maximum size of a University of Arizona department during the Fall 2001 term did not exceed 120 members. Twenty-nine departments were included in the selection pool based on their size and on whether they offered an undergraduate curriculum (this omitted departments in the Colleges of Medicine and Law). Refer to Table 3 for the total departmental selection pool used in this study.

Protocol

Data collection proceeded by first selecting the network boundary, a necessary step in the collection of social network data. The academic environment was selected as the study domain to generate an understanding about how instructors form decisions about engaging in teaching practices. Academe was also the context studied by Friedkin in his initial presentation of the SSI (1998). The network boundary was set at the department level to capture social networks that are defined by disciplinary interests. This chapter details the methods employed to empirically test the stated hypotheses and to investigate the two research questions.

Once the departments were selected, the remainder of the data collection consisted of three phases. First, interviews were set up with either a department head or departmental representative to (1) assess willingness to participate and set up a schedule for data collection and (2) screen behaviors to include in the survey. Second, during the last week of September 2001, a pilot study was conducted on three departments to test the survey instrument. Third, main data collection was conducted in two phases throughout the Fall 2001 term: one fell between the first and second weeks of October, 2001 and the other fell between the first and second weeks of November, 2001.

Interviews with Department Heads

The interviews with department heads were structured to forecast individual levels of willingness to participate in the study and to determine which behavioral domain to use in the survey. Receptivity to participate was a concern because centrality measures are sensitive to incomplete network data; hence it was important to choose departments that were likely to yield the highest possible response rates. Table 4 contains the seventeen departments who agreed to participate in the study.

In addition to assessing willingness to participate in the study, the other goal of the interviews was to determine the behavioral set to use in the survey. In order to derive relative weights for attitude and subjective norm, it was necessary to include measures based on several behaviors. The interviews were designed to identify behaviors that generalize across departmental boundaries to generate one set of behaviors for the survey, as opposed to generating a unique behavioral set per department.

The behaviors discussed in these interviews were limited to those that were considered volitional to all faculty. Volitional behaviors were sought because prediction of behavioral intent is restricted to this type of behavior within the TRA. Behaviors were also limited to those that were accessible to all faculty because, according to Friedkin (1998):

> The assumption of a closed system will be satisfied for the spectrum of issues in which only the members of the defined population have an interest and opinion. Hence, so long as we can postulate such a subset of issues, we can carry forward the analysis. (p. 64)

Therefore the pool of issues included parameters that spanned disciplinary interests and were relevant (i.e., volitional and accessible) to faculty employed by a Carnegie Research I institution. Based on these criteria, the behavioral domains of research and teaching were selected. The second purpose of the interviews was to determine which types of teaching and research behaviors were enacted across disciplinary lines.

Interview data raised two concerns about using research behaviors. First, research behaviors did not seem to generalize across all study participants. It was found that, of the research behaviors that were enacted, few of these behaviors were enacted across departmental boundaries. One explanation is that research behaviors vary according to academic interests within and between departments, and consequently decisions to enact behaviors within this domain may be highly unique to individuals. It was important to select behaviors that were not highly independent across faculty, because such behaviors would intuitively be based on individual attitudes rather than subjective norms regardless of the structural position that an individual occupies. Second, for the research behaviors that did appear to generalize across disciplines, there was little variation in behavioral enactment. Teaching behaviors were enacted by approximately 50% of departmental members and, in contrast, interview data indicated that research behaviors were enacted by approximately 100% of all potential study participants.

Based on these observations, the behavioral domain of research was removed from consideration because it was thought that normative influence is more likely to occur with teaching behaviors as opposed to research behaviors. Teaching behaviors were retained because these behaviors did not appear to have the same complications as research behaviors. Teaching behaviors seemed to generalize across faculty within and between departments, and variation in teaching behavior enactment was reported within departments. To ensure variation in attitude and subjective norm ratings per individual, teaching behaviors were divided between technology and non-technology related activities, and careful attention was paid to creating an equal balance between these two categories. Refer to Appendix A for the list of behaviors included in the study.

Pilot Study

A pilot study was conducted by asking participants to fill out a web-based survey that included measures of network position, individual attitude, subjective norm, and behavioral intention for each of seven teaching behaviors. The departments used in this analysis were selected from the pool of possible departments considered for inclusion in the study. Three departments were included: Plant Science (eight respondents, with a 48% response rate), French and Italian (seven respondents, with a 40% response rate), and Accounting (five respondents, with a 24 % response rate), for a total of 20 participants.

Participants were solicited by distributing letters of introduction that described the study and contained unique login and password information. The login and password information enabled network data collection by providing identifying information for each individual to match respondents with their respective departments. These letters were delivered to each potential participant, identified by departmental membership, by placing a sealed envelope in their campus mailboxes (see Appendix F for initial letter). The purpose of the pilot analysis was to assess scale reliabilities and respondent reactions to the survey. Both issues are discussed below.

Scale reliability was computed for the attitude measure, which consisted of four items designed to tap into behavioral evaluations on seven point Likert-type scales (i.e., pleasant/unpleasant, useful/useless, beneficial/harmful, and easy/difficult). The fourth item, easy/difficult, compromised the scale reliability and was not included in the attitude score. Analysis of the three item attitude scale revealed adequate scale reliability, $\alpha = .81$ for all three departments and across all seven behaviors. Alpha reliability reports across all respondents for each behavior are reported in table 6. Due to the satisfactory reliability of these three measurement items, the attitude scale remained unchanged for the main data collection.

The pilot study was also useful in assessing the survey length. Data showed that the time for completing the survey fell within an acceptable range, from 6 to 38 minutes, with an average of 19 minutes. Although the total time it took to complete the survey was not a concern overall, fatigue was a concern for respondents who identified unusually large personal networks and consequently received a very long survey. Initially, the survey was programmed to present measures for attitude and subjective norm for each individual identified in the social network measure, creating an uncomfortably long survey for individuals who selected many others. Based on participant comments, it was determined that the survey became inappropriately long for these individuals.

In efforts to shorten the measure for the main study data collection, the pilot data were analyzed to estimate how much the survey could be limited in the interest of alleviating respondent fatigue. The data revealed that the number of others identified within the social network measure ranged from 0 to 34, with an average personal network of 15 individuals (SD = 9). The goal was to create a measure that could be completed in twenty minutes or less, since it was expected that respondents would tolerate this demand. This goal guided the decision to limit the list of others included in the measures of attitude and subjective norm. On average, ten others were identified in surveys that were completed in 20 minutes or less, and so the limit was set to ten. This truncation step was applied when individuals identified more than ten others in the social network measure. It was expected that limiting the list of others to ten people increased the data quality. Care was taken to include the ten individuals that created the most salient normative environment within personal networks. For those who identified more than ten others, the survey prompted the respondent to select the ten most important others on the list. Following is the message that appeared when more than ten individuals were selected:

> Here is a list of the individuals you have selected. Even though you have identified [number] people, I am asking you to narrow down this list by selecting 10 individuals. In terms of general teaching practices, select 10 people with whom you have the most knowledge about the teaching practices he or she enacts.

Main Study

As in the pilot analysis, for each participating department, a letter was sent to each individual identified by the department as part of the teaching faculty. The letter described the study and also contained a unique login and password that was required to access the survey. After a period of one week, all respondents were issued a reminder letter regardless of participation. This letter contained the same login and password information and was accompanied by a roll of Lifesavers candy as an incentive. This second letter was intended as a thank you to those who had already participated in the survey and to also encourage participants who had not yet completed the survey to do so. The letter appeared to satisfy both goals. See Appendix G for a sample of the reminder letter.

The survey used in the main study was unchanged, with the exception of adding a measure to limit the number of others identified within the network measure. The alpha reliability for the attitude scale within the main study was computed for each behavior, and the reliability ranged from .71 to .88. These reliability scores were based on the total number of individuals who completed the measure (N=115). Table 6 contains this information. Also, alpha reliability for this measure for all behaviors and for all respondents was .84 (N = 819).

One hundred fifteen participants were included in this analysis, representing instructors from thirteen academic departments. Responses from instructors in the departments of French and Italian and Plant Science, departments initially targeted for the pilot analysis, were also included in the main data analysis. These responses were retained because the response rates exceeded 30% and no changes were made to the survey. Combined with the other eleven departments, the addition of French and Italian and Plant Science produced the thirteen departments included in the analysis. Table 7 contains descriptive information for attitude, subjective norm, behavioral intent, and the estimated weights for attitude and subjective norm.

Analysis Overview

Two major analytic steps were involved in this study. One step contained a derivation of relative weights for attitude and subjective norm for each participant and the other step was a test of whether the relative weight of attitude varied by centrality. Both steps involved random-effects multilevel modeling. This section presents the random-effects multilevel model used in this study and describes the analysis plan for testing the hypothesis and two research questions.

Multilevel Random-Effects Model

This study uses the multilevel random-effects modeling to test whether structural centrality predicts attitude weight. The data structure in the current analysis is similar to the Hedeker et al. study that used multiple observations as a first level variable and individual-level variables of attitude and subjective norm as second level variables (1996). This multilevel structure enables calculation of individual relative weights for attitude and subjective norm, and it constituted the first part of the analysis. However, the goal was to go beyond detecting individual level variation in relative weights by adding centrality as a predictor variable. Adding centrality created the third level of the multilevel model. In this section, the specification of this three level model is reviewed along with a description of how the regression model used in this analysis was constructed.

The first step in constructing a multilevel model is in defining which variables belong at each level. Figure 4 illustrates the three levels included in the current multilevel analysis. This illustration contains information on the units associated with each level, on the variables specified at each level, and on whether the variables were treated as fixed or random effects in the analysis. This section provides the rationale for the variable specification for each level of the model.

Level 1 Specification: Multiple Observations

Including a random-effects component in a multilevel model enables calculation of individual relative weights for attitude and subjective norm (Hedeker et al., 1996). Obtaining the contributory influence for the behavioral determinants of attitude and subjective norm for each individual is an improvement over assessing these weights based on aggregate data because this procedure allows a test of individual variation in relative weights (Hedeker et al., 1996). By deriving a weight for attitude for each individual, the random-effects component also enables a test of the SSI assumption that an individual's attitude weight is a function of his or her centrality score.

This task was accomplished by following the method introduced by Hedeker et al. (1996). The purpose of their study was to illustrate the existence of individual variation between the relative contribution of weights associated with attitude and subjective norm. This required a design that enabled estimation of these relative weights for each individual, which was satisfied by a random-effects model that was based on a repeated measures design (Hedeker et al., 1996). In their study, the repeated measures were multiple observations of attitude and subjective norm for each individual across four time points. Treated as levels of a random variable, these multiple measurements served as the source of individual level variation used to calculate the relative contribution of attitude and subjective norm toward the formation of behavioral intentions.

Similar to the methods used within the Hedeker et al (1996) study, the analysis for this study included a random-effects component. However, rather than using time to represent the multiple levels of this variable, multiple observations were based on a set of seven teaching behaviors. Using multiple observations for each individual created an independent regression for each individual that was based on the seven behaviors. This allowed for the derivation of individual-level relative weights of attitude and subjective norm, represented by the regression coefficients for each independent variable. The regression coefficients that represented the relative weights of attitude and subjective norm are estimated 'in practice' by conducting iterative numerical procedures.

Bayes estimation was used to describe the variance-covariance structure of the random-effects variable (Bryk & Raudenbush, 1992). Traditionally, a compound symmetry model, also labeled as a homogeneous covariance structure, is used to represent the covariance structure in repeated measures designs. This model type treats the variance and covariance as constant among the levels of the random variable, known as 'standard constant sigma-squared.' Hence, the compound symmetry model implies that all variances are equal across the levels of the repeated measure. Other covariance structures include unrestricted, which allows the variation in the random factor to freely vary, heterogeneous, which allows for variation in correlations among the levels, and autocorrelated models, which allow for systematic specification of covariance among the levels that is common in time series data. Determining which description best fits the covariance structure was accomplished by conducting a model comparison approach, and a goodness of fit test identifies which type of covariance structure best fit the data.

Level 2 Specification: Attitude and Subjective Norm

The second level contained variables representing individual perceptions of behavioral intent, attitude and subjective norm. Measures for each of these variables were obtained on seven teaching behaviors. Attitude was included in the model because it is one of two behavioral determinants as specified within the TRA. It was included at the this level because it represents each individual's evaluation of a set of teaching behaviors relative to behavioral intent. Subjective norm, the second determinant of behavioral intention, was also included at this level because it was based on individual level perceptions about the attitudes 'important others' hold about performing a set of teaching behaviors.

Level 3 Specification: Structural Centrality

The third level contained individual scores of structural centrality. A centrality score was derived for each individual in the study, just as each individual was assigned a weight for attitude and subjective norm. Attitude and subjective norm were placed at the second level in this model because they were derived from information at the first level: multiple observations. Centrality was placed at the third level in this model because this variable was derived from departmental information. Therefore, although a centrality score is obtained for each individual, centrality scores represent a macro-unit relative to the individual perceptions of attitude and subjective norm, which are micro-units.

This specification runs counter to the common conception of levels of analysis, a term typically used to describe different sources of information. For instance, individuals are placed at one level while dyads are placed at another level. Traditional use of the term would mean that the data collected in this study would still divide into three levels, but the variables at the third level would focus on departmental level information, such as network density. In contrast, the third level variable in this data analysis is structural centrality, a score assigned to each individual within the network. It is placed on the third level because it is based on departmental information, which is a third level source of information. Figure 4 illustrates the multilevel model used in this study.

Random Versus Fixed Variables

The decision of whether to treat variables as fixed or random was based on determining whether the levels of the variable in this study were replaceable with equally acceptable levels (Jackson & Brashers, 1994). At the first level, the multiple observations were treated as random because the levels of this variable hold no interest in this analysis other than their ability to represent one of any number of teaching behaviors. These multiple observations are expected to vary across individuals across a series of measurements. In time series designs, the multiple observations are defined as points in time; however, multiple observations can also occur across multiple measurements taken at one point in time. In this study, it was expected that the scores derived from the measurements of seven teaching behaviors would randomly vary within individuals.

By definition, the second level variables of behavioral intention, attitude, and subjective norm were also random. However, multilevel analysis of repeated measure multilevel models fixes the variation of these level 2 variables because the random variation is "absorbed" into the first level variable (Bryk & Raudenbush, 1992). The third level variable, centrality, was located at the departmental level of analysis and was treated as fixed in this model because (a) departmental membership was aggregated, consequently removing the variation among departments on this variable, and (b) the variable was forced as fixed by the multilevel software used for this analysis (HLM5).

Summary of Variable Specification

In sum, the data for the current study fall into three levels: multiple observations (1), individuals (2), and departments (3). Multiple observations are located at level 1, which are nested within individuals at level 2, who are nested in departments at level 3. The relationship between level 1 and 2 is that behaviors are nested in individuals. In terms of macro and micro units, behaviors are micro-units and individuals are macro-units. This relationship was the basis for the random-effect, from which the regression weight for attitude and subjective norm was generated.

The relationship between levels 2 and 3 represented individuals (micro-unit) nested in departments (macro-unit). This second macro-micro relationship, between levels 2 and 3, constituted the basis for the hypothesis test conducted in this study. The hypothesis test entailed a cross-level interaction between levels 2 and 3: centrality (level 3) was specified to predict the regression slope of attitude (level 2). The level two variables were the regression weights for attitude and subjective norm. In other words, the level 3 variable of centrality was specified to interact with the slopes of the level 2 attitude, creating a 'slopes as outcomes' model; the slope at level 2 is treated as the dependent variable and the level 3 variable of centrality is the independent variable. Figure 5 illustrates the macro-micro proposition tested in this study, which specifies a cross-level interaction between the level 3 variable of centrality and the attitude slope.

Model Construction

The regression equation used in this study was based on the TRA model. Behavioral intention was the dependent variable and the independent variables were attitude and subjective norm. Behavioral intent was regressed onto attitude and subjective norm, and relative weights for the individual variables were represented by the regression coefficients generated within the equation. To facilitate a description of how the model was constructed for this study, the traditional TRA model is reviewed:

$$\text{Behavioral Intent}_i = \beta_0 + \beta_1\text{Attitude}_i + \beta_2\text{Subjective Norm}_i + r_i$$

In this model, *i* represents individuals and the slopes, β_1 and β_2, represent the expected change in behavioral intent associated with a unit increase in attitude or subjective norm, respectively. Although this equation is effective for deriving the relative weights for groups of individuals, it does not allow for the specification of individual weights. Individual weights were necessary to determine the relative contribution of attitude and subjective norm in relation to behavioral intention, and these weights were computed by adding a term into the model that represented attitude and subjective norm weights for each individual. At a conceptual level, the regression equation below illustrates how individual effects are accommodated within the model (Hedeker et al., p. 110):

$$\text{Behavioral Intent}_i = \beta_{0i} + \beta_{1i}\,\text{Attitude}_i + \beta_{2i}\,\text{Subjective Norm}_i + r_i$$

The effect of attitude on behavioral intent for each individual is represented by β_{1i}, and the effect of subjective norm on behavioral intent for each individual is represented by β_{2i}. Although the above model illustrates how individuals are represented in the regression model, it does not enable estimation of the relative weights between attitude and subjective norm because it is based on one measurement occasion. Just as a normal regression cannot be estimated with one data point. Individual regression weights cannot be estimated in a model with just one measurement or observation of a single behavioral intent. Instead, multiple measurement occasions are necessary to obtain this estimation. Individual-level weights for attitude and subjective norm can be estimated, in principle, if multiple behaviors are evaluated or a single behavior evaluated over time. This next model illustrates how the regression equation is constructed to accommodate multiple measurement occasions for the purpose of deriving individual relative regression weights for attitude and subjective norm, where *j* represents a repeated measure:

$$\text{Behavioral Intent}_{ij} = \beta_{0i} + \beta_{1i}\,\text{Attitude}_{ij} + \beta_{2i}\,\text{Subjective Norm}_{ij} + r_{ij}$$

Now that the regression model is tailored to accommodate individuals and to derive individual level weights for attitude and subjective norm, the model was further expanded to include a predictor of the relative weights. The predictor of interest in this study was one's position within a network that was defined by the centrally score. The SSI assumes that centrality predicts attitude weight, which predicts behavioral intent. Adding centrality creates another layer within the multilevel configuration. The first level of the model is made up of the multiple observations per individual and ratings of behavioral intent, attitude, and subjective norm represent the second level. Centrality is placed at the third level, and this variable is modeled as a predictor of the slope for the attitude variable at level 2.

A relationship between centrality and the regression coefficient for attitude was specified, which involves a shift in the regression model up one level where the regression coefficient for the independent variable of attitude measured for each person is now treated as the dependent variable and centrality is specified as a predictor of this variable. In other words, the outcome variable is the regression slope (Bryk & Raudenbush, 1992). Among the types of macro-micro propositions enabled by a multilevel model, this analysis uses a cross-level interaction between centrality at level 3 and attitude weight at level 2. The model used in this analysis differs from the previous example because a third level is added which contains a predictor of the level 2 slopes. In hierarchical form, the model is specified as:

Level 1 & 2: $\text{Intent}_{ij} = \beta_{0i} + \beta_{1i}\,\text{Attitude}_{ij} + \beta_{2i}\,\text{Subjective Norm}_{ij} + r_{ij}$

Level 3:
$$\beta_{0i} = \beta_{00i} + \beta_{0i}\,\text{Centrality}_i + u_{0ij}$$
$$\beta_{1i} = \beta_{10i} + \beta_{1i}\,\text{Centrality}_i + u_{1ij}$$
$$\beta_{2i} = \beta_{20i} + u_{2ij}$$

where:

β_{00i} represents the average intercept across the level 3 units
β_{10i} represents the average regression slope across the level 3 units for attitude
β_{20i} represents the average regression slope across the level 3 units for subjective norm
u_{0ij} represents the unique increment to the intercept associated with level 3 unit $_j$
u_{1ij} represents the unique increment to the attitude slope associated with level 3 unit $_j$
u_{2ij} represents the unique increment to the subjective norm slope associated with level 3 unit $_j$

Analysis Plan

Data analysis for the hypothesis test involved three stages. First, the variance component for attitude and subjective norm was tested using a model comparison approach. Second, an intraclass correlation was conducted on the centrality scores to determine the feasibility of aggregating centrality scores across departments. Third, a cross-level interaction test was conducted within a random-effects multilevel model. These three stages are described followed by a description of the analysis plan for the research questions.

Variance Component Test

Multilevel modeling allows for tests of variance through a model comparison approach, also known as a 'variance component' hypothesis (Bryk & Raudenbush, 1992). The variance component test provided information about whether or not the contributory weights for attitude and subjective norm vary among individuals. This test simply informs about the variance among the weights for attitude and subjective norm. The practice of multilevel analysis suggests evaluating whether significant variance is detected among variables at one level before specifying predictors of this variance at a higher level (Bryk & Raudenbush, 1992). In kind, the variance component test was conducted on the attitude and subjective norm weights to determine if specifying a third level predictor was feasible. An example of a variance component test is seen in Hedeker et al.'s study, which tested a variance component hypothesis that stated that individuals vary in their relative weights when forming a behavioral intention (1996). As they put it:

> [T]o test the TRA assumption (the null hypothesis of whether $\sigma^2\beta_2 = 0$ and $\sigma^2\beta_3 = 0$ can be rejected or not), we first fit a model setting these two variance components and all related covariance terms equal to zero... Next, we allowed the effects of ATB and SN to vary with individuals. (p. 113)

In other words, two models were compared: one model treated the components of attitude and subjective norm as fixed and the other treated the components as random. The variance component was estimated for both models and each was assessed regarding the degree to which they predicted the model variance. This degree is measured by the deviance score, which is an indicator of the model fit: higher deviance indicates a poorer fit (Bryk & Raudenbush, 1992). For the purpose of model comparison, the deviance score associated with each model is the basis of comparison, and the model that offers a significant reduction in deviance indicates a comparatively better fit with the data. The following test statistic is used to compare the deviance scores and D_n indicates the deviance score for each model:

$$\text{Model Fit} = D_0 - D_1$$

Significance between the deviance scores is tested with a chi-square. "Large values of the statistic are taken as evidence that the null hypothesis is implausible and that the null model is therefore 'too simple' a description of the data" (Bryk & Raudenbush, 1992, p. 58).

In Hedeker et al.'s study, the data were best fit by a model whose components are treated as random (1996). Their results illustrated that the model that allowed the weights to vary across individuals offered the best fit of the data, leading to the conclusion that the weights for attitude and subjective norm varied per individual. This procedure was replicated in the current study. In addition to determining whether attitude and subjective norm components should be treated as fixed or random in the multilevel model, this variance component hypothesis also functioned to offer support for Hedeker et al.'s findings (1996).

Intraclass Correlation Test

The second step of the analysis was to assess the feasibility of combining the centrality scores across departments. Doing so allowed for the inclusion of more data points for the hypothesis test. Pooling the data was only possible if these scores were not interdependent; otherwise aggregating the data would contribute error variance in the cross-level interaction test and also make tests of significance unreliable (Kashy & Kenny, 2000). Within multilevel analysis, the intraclass correlation is used to test the extent to which there are differences between upper level units in their average scores on Y when X and Z are controlled (Kashy & Kenny, 2000). A significance test of the intraclass correlation coefficient determines whether the centrality scores are independent across the departments. A significant intraclass correlation would indicate that the data were interdependent within the departments, and consequently the data could not be aggregated. A nonsignificant intraclass correlation would provide some warrant for aggregating the data across departments.

Calculating the intraclass correlation began with fitting a one-way ANOVA model to determine the amount of variability in the centrality scores within and between departments. The two sources of variance estimated in the ANOVA model were then used to calculate the intraclass correlation of the centrality scores. The formula for the intraclass correlation for group data is presented below; G indicates the group variables, S indicates participants, and n indicates group size (Kashy & Kenny, 2000):

$$\hat{p} = \frac{MS_G - MS_{S/G}}{MS_G + (n-1)MS_{S/G}}$$

In the case of a nonsignificant intraclass correlation, the second step in the analysis would entail pooling the scores across the upper-level units (i.e., pool centrality scores across departments).

Hypothesis Test. The hypothesis was tested by a cross-level interaction between the macro-unit variable of centrality and a micro-unit variable of attitude weight. The macro-unit variable of centrality was specified to predict the regression slope of the micro-unit variable of attitude. This interaction test was used to reveal whether increases in centrality scores relate to increases in attitude weight.

Research Questions. The first research question concerned whether these weights varied across the seven behaviors used in the study. Two approaches were used to address this question. First, an interaction term was specified between behavior type and attitude weight to test for variation across behaviors as a function of behavior. An interaction between behavior type and the weight for attitude was specified to evaluate whether this weight varied across behaviors. An interaction between behavior type and the weight for subjective norm was also specified to evaluate whether the subjective norm weight varied across behaviors. The coefficients for these interaction terms in the regression model indicated whether the weights for each independent variable (attitude and subjective norm) varied across behaviors. This strategy mirrors the one used by Hedeker et. al (1996), which used an interaction term to represent changes across levels of a random variable in the model. Also mirroring Hedeker et al.'s method, the MIXREG program was used in this analysis. The second strategy used to address this research question involved running a TRA model in a regression analysis for each behavior for the purpose of comparing the relative weights. The second research question inquired about the relationship between self-reports of relative weights and the empirically estimated weights. This question was addressed by computing a Pearson Product-Moment correlation between self-report scores and scores representing the difference in estimated weights.

CHAPTER 4: RESULTS

This chapter details the data analysis results for the hypothesis test and two research questions. Three elements were involved in the hypothesis test. First, the results for the variance component hypothesis are presented. Second, results from the intraclass correlation calculation are presented. Third, the results from the cross-level interaction test are presented. The remainder of this section reviews the information relevant to the two research questions.

Hypothesis

Variance Component Test

A model comparison approach was used to test for variance at the individual level. Two multilevel models were compared that specify whether or not the variance among individuals is random. The empirical Bayes methods used to estimate the individual relative weights were automatically generated in MIXOR, the multilevel modeling software program used for this analysis (Hedeker et al., 1996). Table 7 contains summary information for these Bayes estimates for attitude and subjective norm, and Figures 6 and 7 contain descriptive information.

The fixed model restricted the variation to zero and the random model allowed the variance to freely vary among individuals. The deviance score (D_0) for the fixed model = 1983.63 and the deviance score for the random model (D_1) = 1960.88, for a difference of 22.75 (refer to Table 8 for the fixed model results and to Table 9 for the random model results). With 3 degrees of freedom the χ^2 value is 7.815, significant at the $\alpha = .05$ level (see Table 10). Due to the statistically significant reduction in model deviance, this result indicates that treating the model components as random provides a better fit of the data compared to the fixed model, leading to the conclusion that individuals vary in the relative weights of attitude and subjective norm. This replicates the findings that individuals vary in their attitudinal and subjective norm weights relative to behavioral intentions (Hedeker et al., 1996).

In addition to assessing the variance components of attitude and subjective norm variables as they varied among individuals, the model for the covariance structure for the levels of the random-effect was assessed by a model comparison approach. The multilevel modeling software used in this analysis (HLM5) specified three types of covariation structures to model the covariance among the levels of the random-effect variable specified in the model: unstructured, heterogeneous, and homogeneous (which is analogous to the compound symmetry model). To test for the best model fit, the deviance scores for each covariance type were calculated. The unstructured deviance (model 1) = 1838.13, the homogeneous deviance (model 2) = 1929.59, and the heterogeneous deviance (model 3) = 1908.43. The unrestricted model offered the best fit of the data, as indicated by the significant $\chi 2$ for the two sets of model comparisons. Model 1 is a better fit than both model 2 ($\chi 2 = 91.47$, df = 26, $p < .05$) and model 3 ($\chi 2 = 70.30$, df = 20, $p < .05$). Tables 11 through 13 contain the unstructured, heterogeneous, and the homogeneous covariance matrices, respectively. Table 14 presents the model comparison output.

Intraclass Correlation Among Centrality Scores

The first step in calculating the intraclass correlation was to fit a one-way ANOVA model to determine the amount of variability in the centrality scores within and between departments. The source table for this ANOVA model contains the estimated sources of variance required to calculate the intraclass correlation (Table 15). Using the intraclass correlation formula proposed by Kashy et al (2000), the intraclass correlation among the centrality scores across the 13 departments was .024. This correlation is not statistically significant, $\hat{p}$ = .024, F (12, 102) = 1.21, p = .278 and n = 8, the average number of group participants. Since this intraclass correlation was small and nonsignificant, the simplified analysis was used for the hypothesis test. Furthermore, an intraclass correlation was calculated for the relative attitude weights among departments, and it was not statistically significant, $\hat{p}$ = -.054, F (12, 102) = .170, p = .99 and n = 8, the average number of group participants (refer to Table 16 for the ANOVA source table for attitude weight).

The intraclass correlation was not statistically significant for the centrality scores nor for the relative attitude weights; consequently the data were pooled across departments. Table 17 contains the pooled mean and standard deviations for each of the seven behaviors based on the combined 115 individuals. Table 18 contains means and standard deviations for individuals pooled across department, for all behaviors.

Descriptive data on behavioral intent, attitude, and subjective norm for each teaching behavior and by department are presented in Tables 19 through 21. Table 22 presents the individual scores for centrality and attitude weight per department. The correlations between attitude weight and centrality by department are presented in Table 23, and descriptive data for the centrality and attitude weights per department are presented in Table 24.

Cross-Level Interaction Test

The hypothesis specified a relationship between centrality and the regression slope of the relative attitude weight: as structural centrality increases, the weights associated with attitude will increase. This hypothesis was tested by a cross-level interaction where, at level two, the relative weight of attitude, derived from multiple observations toward performing a set of teaching behaviors, was regressed on the third level variable of structural centrality. The interaction test informs whether or not centrality predicted the slope related to the attitudinal component with the TRA model.

The cross-level interaction test was conducted with two software programs, MIXREG and HLM5, and the results from both programs were comparable. Both programs are based on maximum likelihood estimation, and the calculation of the Bayes estimation is identical except that MIXREG adds the mean of the random effects to the empirical Bayes estimates and HLM5 does not. Therefore, differences were not found in the results produced by each program. The interaction test was based on the unstructured correlation matrix for the behavior variable. This interaction test was not statistically significant ($t = .764$, $p > .05$, $df = 113$), indicating that structural centrality did not predict variation in individual relative weights of attitude. Both sets of output are reported in Table 25. The power of this cross level interaction test was approximately .50, and a description of how power was estimated is presented below. Additional support was provided by a model comparison between the multilevel model and the traditional TRA model. The model containing the interaction term for structural centrality by attitude weight did not result in a comparatively better fit of the data (see Table 26 for model comparison results).

Descriptive analysis of the relationship between the relative attitude weight and structural centrality further illustrate that the data did reflect the expected relationship defined in the SSI. Scatter plots of the weights for attitude and subjective norm, represented by empirical Bayes estimates, by structural centrality scores illustrate that the data do not reflect a positive linear relationship between these two variables (see Figures 6 and 7). Also, a scatter plot of the expected relationship between centrality and attitude weights and the observed relationship is presented in Figure 8. The obtained data came from the survey responses and the expected data were calculated with the following SSI formula, where w_{ii} = attitude weight and c_i = structural centrality:

$$w_{ii} = 1 - \sqrt{(1 - c_i)}$$

Power

The power of a test is a measure in how effective it is in detecting an effect in the population studied. In other words, power is the risk one takes of not rejecting the null hypothesis when it is false. Power is related to effect size, the sample size of the population and the specified alpha criterion for determining statistical significance (Cohen & Cohen, 1983). The following information was used to compute Cohen and Cohen's power for the cross-level interaction test within this study: the sample size (N=

115), the alpha criterion was .05, and the effect size was computed based on the *t* values generated from multilevel analysis output (Karney & Bradbury, 1997; Rosenthal & Rosnow, 1984). The t value for the interaction between centrality and attitude weight was .764 with 113 *df.* This information enables the calculation of the effect size for this interaction with the following formula (Rosenthal & Rosnow, 1984):

$$r = \sqrt{{t^2}/{t_2 + df}}$$

$$.07 = \sqrt{{.584}/{113.584}}$$

Hence, an effect size of .07 was obtained for the cross-level interaction test. This information was used to calculate power with Cohen and Cohen's formula (1983):

$$N^* = {L}/{r} + k + 1$$

Where N* = optimal sample size in light of desired power level, L = a value based on power level, *r* = effect size, and *k* = degrees of freedom. The value for L was determined by a table that provides values for L as a function of α and power expectations (Cohen & Cohen, 1983). According to the table, the power for a sample size of 114 participants equals .50 (L = 13.62). Because 115 participants were included in this analysis, the power of this test was .50, which represents moderate power to detect a difference in the population if it existed (Cohen & Cohen, 1983).

Although Cohen's power formula is sufficient for unilevel models, in the case of multilevel modeling the power estimation must be altered to include the impact multiple levels have on the estimated power of the test. Design effect is the term used to describe the effect of adding additional levels in a multilevel model. In other words, the design effect is defined as "the factor by which the variance of an estimate (which is the square of the standard error of this estimate) is increased because of using a two-stage sample rather than a simple random sample with the same total sample size" (Snijders & Bosker, 2000, p. 23). And, the "design effect is also the factor by which total sample size needs to be increased to achieve the same estimation variance… as a simple random sample of the given size" (p. 143). The design effect for a multilevel model allows researchers to assess the optimal sample size for multilevel models. The formula for the design effect (Snijders & Bosker, 2000) is:

$$\text{design effect} = 1 + (n - 1)\,\rho_i$$

Where n = the average sample size in the second stage of the sample and ρ_i = the intraclass correlation. The standard deviation for centrality scores is .096 and the standard error = .03 (e.g., $.096/\sqrt{n}$). Based on these figures, the sample size for the first level should be $n = 1/(.03^2)$ = 1111, which is a larger figure than what was collected in the study (e.g., 115 observations of seven teaching behavior resulted in 805 data points).

Estimation of the optimal sample size is altered when a second level is added to the model. For the current design, the first stage represents the seven teaching behaviors and the second stage represents the number of survey respondents. There were 115 survey respondents. Information that is required to compute the design effect is the intraclass correlation among the centrality scores in the second level (ρ_i = .024), the standard deviation for centrality (*sd* = .096), and the standard error, which was .03. Also required is the average group size at the second level (group size average = 8). Given this information, the design effect is: 1 + (7) .024 = .19.

This design effect aids in estimating the sample size necessary for future tests of the SSI that uses a similar multilevel model. With two stages of sampling, the design effect is the product of the estimated N from the first stage (N=1111) by the design effect (design effect = .19), which results in an optimal sample size of 211. This number reflects the sample size necessary to achieve the same precision as a one-stage model and indicates that an increase from 115 to 211 respondents at the third level of the model would increases the power for the hypothesis test in this study.

Calculations for power in two level designs is possible, and Snijders and Bosker have authored a program (PINT – Power In Two level designs) that is designed to make this estimation (2000). However, power calculations (as well as calculations of the design effect) become more complex with multilevel designs that include a repeated measure as a random-effect at level 1. In the case of this analysis, the first level was represented by a set of seven behaviors that were treated as random, constituting a sample of seven behaviors out of a population of possible behaviors that fall within the domain of teaching practices. A sampling of individuals represented the second level, and departments represented the third level. The complexity of a power analysis for this model is due to these different samples, considering that the seven behaviors the first level were in one way treated as a sample of behaviors from a population and in another way they were treated as a variable in the analysis of which a sample of individuals respond to attitude and social norm ratings for each behavior.

In sum, power, which was calculated with the use of an approximate measure for the multilevel design, was moderate. Also, upon evaluating the impact of the multiple levels used in the analysis, it appears as if an increase of 96 participants would have increased the power of the study. However, there is a need to develop reliable calculations of power that will accommodate the complexities involved with random-effects multilevel modeling. It is expected that once the use of multilevel random-effects modeling increases, more precise procedures for assessing sample size will become available. Until that time, these estimates are the best guesses available for estimating the power of the hypothesis test.

Research Questions

Research Question #1

The first research question inquired about whether the relative weights for attitude and subjective norm varied across the seven behaviors used in the study. Two interaction tests were conducted to address this question. Both are two tailed, as the main interest in these tests was to evaluate whether behavior type was related to the attitude and subjective norm weights as opposed to specifying the direction of the weights. The interaction between behavior type and attitude weight indicated that behavior type was not associated with variation in attitude weight when setting the alpha at .05 ($z = -1.698$, $p = .09$). Although not significant at this level, this result is suggestive of some variation between the behaviors if a more liberal criterion of .10 were to be applied. The interaction between behavior type and subjective norm weight presented more concrete evidence that behavior type was not associated with variation in this variable, $z = .119$, $p = .91$). Table 27 contains the output for these tests.

The interaction tests informed whether attitude and subjective norm weights varied across behavior type, and results suggest that there was no significant variation in these weights across behavior. Another way to examine whether or not the weights for attitude and subjective norm were in the same direction across behaviors, a traditional TRA regression model for each behavior was run. The traditional regression aggregates the data, which produced one set of relative weights for attitude and subjective norm for each behavior type across all individuals included in the study regardless of their network position or departmental membership. The results show that although there is a suggestion that there are differences between behaviors between these weights, the data show that the attitudinal component consistently had a higher contributory weight in comparison to subjective norms across the seven behaviors. See Table 28 for relevant output.

Research Question #2

The second research question inquired about the relationship between a self-report measure of relative weights and empirically estimated weights. To compare these measures, a correlation was calculated between the score obtained by the single item self-report measure (ranging from 1, indicating a heavier weight on subjective norm and 7, indicating a heavier weight on attitude) and the difference score between the empirically estimated weights for attitude and subjective norm. The Pearson Product-Moment Correlation between these two scores was .02, $p = .87$, indicating that there was no association between the self-report weight and the difference score between attitude and subjective norm.

CHAPTER 5: DISCUSSION

This study of social influence explored one explanation for how two influence sources, attitude and subjective norm, contribute to the formation of behavioral intent. The theory of reasoned action and the diffusion of innovations theory both aim to explain and predict behavioral outcomes. The TRA offers micro level predictors based on individual perceptions of performing a behavior and diffusion of innovations theory introduces a multilevel perspective on behavioral outcomes as a function of decision contexts. However, these theories do not include an account for conditions under which either source of influence leads to behavioral decisions, and the goal of this study was to test a predictor of these relative weights.

The findings of this study suggest that interpersonal influence processes may not operate as expected. The SSI assumes that central individuals are influential over others, and therefore they should be less susceptible to normative influence. The self-other balance suggests that a high weight on one source of influence necessitates a low weight on the other, implicating that less susceptibility to normative influence necessitates a high susceptibility to attitudinal influence. Structural centrality is also considered a strategic network position within diffusion of innovations theory; opinion leaders are integrated within a diffusion context and they exert influence due to their structural position.

The results of this study encourage scrutiny of the SSI assumption. The data also suggest that diffusion of innovations may depend network properties that extend beyond those stipulated within the theory, providing additional insight for what an ideal diffusion context. This discussion focuses on the theoretical implications for the SSI and diffusion of innovations theory. It also includes an inquiry into what *does* influence the relative weights of attitudinal and normative influence. An evaluation of the study limitations offers guidance for how to create stronger tests of the self-other balance, and future directions for how to reveal predictors of the self-other balance are also presented.

SSI Implications

The SSI presents one possible predictor of the relative weights between attitudinal and normative influence. The assumed relationship between structural centrality and attitude weights is only one piece of a larger theory, which suggests systems of interpersonal influence that span across interconnected networks and across time. The SSI contributes to the theoretical environment of interpersonal influence and behavioral outcomes in three important ways.

First, by basing micro-level outcomes on macro-level predictors, the SSI offers a multilevel theory of influence that has potential to provide a comprehensive representation of interpersonal influence contexts. Macro level features of this theory include one network position (structural centrality), as well as network properties (network density). Micro level features include attitudinal and normative influences. The assumed relationship between structural centrality and attitude weights represents a cross-level interaction between macro and micro levels of analysis. This study presents a test of this multilevel model that is based on measured attitudes and subjective norm. The methods used in this study can also include exploration into other network positions and properties that may influence individual level behavioral choices, which is a direction for future theoretical development on explaining the self-other balance.

Second, the SSI offers an explanation of interpersonal influence that extends current theory. In terms of the TRA, adding structural predictors extends the theoretical system of individual behavioral choice within a social context of influence that is not modeled within the TRA. The role of normative influence can be explored with the addition of structural variables. For example, social network ties can represent an objective influence context, which can be compared to the role of subjective normative influences. Addressing the impact of subjective versus objective normative influence over behavioral intent has potential to extend theorizing about how influence processes occur. In terms of diffusion of innovations theory, the SSI stipulation offers an explanation of individual level choice processes as a function of network position, which motivates inquiry into what makes opinion leaders influential over others and also what makes individuals who are not opinion leaders more susceptible to normative influence.

Third, this theory introduces a theoretical mechanism that explains sustained behavioral enactment. Although the SSI does not have an explicit behavioral element, it easily accommodates the explanation of behavioral outcomes. Including a behavioral element into the SSI highlights the contribution of this theory relative to the TRA and diffusion of innovations theory. The difference among these theories hinges on behavioral enactment: Both the TRA and diffusion of innovations theory focus on predicting individual–level behavior at one point in time, and the SSI proposes a equilibrium relationship between attitudinal and normative influence that explains behavioral enactment over time. The SSI fulfills a need of explaining sustainability of behavioral enactment through this equilibrium relationship, which is an important contribution to theoretical work on explaining behavioral outcomes.

All three of these contributions make the SSI a promising theory of interpersonal influence. However, the findings of this study raise some doubt about one assumption within this theory. The results of this study suggest that the formal model of the self-other balance may not reflect how influence processes occur.

As an illustration, figure 9 contains a prototypical faculty network derived from the social network data. The nodes represent individuals: The smaller nodes on the periphery represent individuals with low structural centrality scores and the larger nodes in the center of the network are in positions of high structural centrality. Attitude and subjective norm weights were derived for each individual who completed the entire survey and this network includes the difference scores between these weights for each individual who completed the entire survey (represented by the triangle-shapes). In investigating the distribution of these difference scores across this network, it is evident that the attitude weights are heavy for individuals in both central and non-central positions. There is little variation in the relative contribution of attitude among central individuals and peripheral individuals, a result that raises doubt about the strength of the self-other balance assumption.

In sum, the SSI offers a powerful theory of influence that has potential to expand current perspectives; however findings suggest that the assumed predictor of attitudinal and normative weights may not exist as expected. Potential limitations of the theory, in particular the possibility that the formal model does not represent how influence processes occur, motivate investigation into what else may explain the relative contribution of attitudinal and normative influence. This effort can improve the SSI by suggesting a set of scope conditions that will describe when the relationship between structural centrality and the self-other balance will occur.

Alternative Predictors

In light of these findings, a question remains as to what influences the relative contribution of attitudinal or normative influence. The relative weights of these influence sources may be due to something other than, or in addition to, structural position. Although not designed to evaluate other possible explanations, this study does offer some information that might help identify important influences. Several such influences are considered below.

Individual Factors

It is reasonable to speculate that individual level variables lead to the predominance of one influence source over another. Research suggests that individuals can be classified by their tendency to fall under attitudinal and normative control (Trafimow & Finlay, 2001a; Trafimow & Finlay, 2001b). One explanation of this difference can be due to an individual's sense of power or status within a social network. Individuals of high status may be under attitudinal control and those of low status may be under normative control. This relationship was tested in the data collected in this study by comparing attitude weights against an indicator of status: departmental rank.

A cross-level interaction was tested between rank and attitude weight to explore whether or not status serves as a predictor. Rank was operationalized by each participant's title, which included Adjunct, Visiting, Assistant, Associate, and Full Professor. Visiting professors were assigned the lowest rank because, although they may have a high rank in their home institution, these individuals were assumed to have little power to influence others opinions due to their assumed short tenure at the university. Moreover, these professors, due to their visiting status, may not have had time to develop influential ties within the department. Results indicate that rank is not a predictor of attitude weight, $t = .07$, $p = .94$ (Table 29 contains output of this test of alternative hypothesis). Although individuals may vary in their tendency to be under normative or attitudinal control, the weights obtained in this study do not depend on rank, which was expected to be possible predictor of this individual difference variable.

Also, these data allowed for investigation into the relationship between centrality and status. Central individuals are expected to wield interpersonal influence, and it follows that centrality will be related to rank. The relationship between these variables was explored by conducting a correlation analysis between centrality and rank. The data reveal that there is no significant correlation between these scores ($r = .014$, $p > .05$, $n = 115$). Moreover, the nonsignificant correlation between rank and centrality suggests that centrality may be based on dimensions other than status when it comes to teaching networks.

Another individual level predictor of which source of influence dominates a decision is the type of motivation employed. The Heuristic-Systematic Model of persuasion introduces different types of motivation that drive information processing (Eagly & Chaiken, 1993). Accuracy-motivation describes the tendency to attend to information about an issue in efforts to make the best judgment. Impression-motivation describes the tendency to focus on what others think in efforts to please others within the influence environment. Essentially, these two types of motivation are aligned with the two types of influence: accuracy-motivation relates to informational influence and impression-motivation relates to normative influence.

Individuals may vary in their motivation, which could lead to the reliance of either informational or normative influences. The data collected in this study show that individuals are likely to base decisions on informational influence rather than normative influence, indicating that perhaps accuracy-motivation was employed. However, research has yet to show whether these motivations are an individual trait or a feature of the context in which a decision is made, or perhaps both conditions could concurrently influence the reception of information. Hence, the data do not indicate whether this motivation is based on an individual's tendency to be accuracy-motivated or on the decision context (such as the need to be accurate about making a correct decision).

Individual level perceptions about performing a behavior also ought to impact which source of information is used to make a decision. In particular, perceptions about behavioral characteristics may induce different searches for information. Three factors are discussed which are expected to lead to attitudinal or normative control: issue uncertainty, issue importance, and the susceptibility principle (Eagly & Chaiken, 1993). It is known that uncertainty leads to reliance on information sources. If the uncertainty is regarding a socially based issue, then normative influence will dominate the decision outcome. If uncertainty is resolved though research and the collection of evidence, then informational influence will dominate.

Uncertainty is related to the importance of the behavioral decision. Unimportant decisions that are uncertain may be influenced by normative influence, and important uncertain decisions may be influenced by attitudinal influence. Work on information-seeking behavior has found that the search for information is a function of the perceived benefits of obtaining that information (Morrison & Vancouver, 2000). Therefore, information is sought out to the degree that it is important and beneficial to the individual. Based on the notion that uncertain and important behaviors will trigger the search for informational influence, one interpretation of the results is that teaching behaviors hold these qualities. However, the data collected do not reveal whether each behavior was perceived as uncertain or important, which suggests that this should be done in future study.

According to the Heuristic Systematic Model of persuasion (HSM), the choice to use attitudinal or normative information is based on the sufficiency principle (Eagly & Chaiken, 1993). The sufficiency principle states that the search for information will be driven by a need to gather sufficient information to make an acceptable judgment. Individuals employ economy in their information search and will initially turn to social information to make a judgment. If adequate information is not provided by the social information source, then the search for additional information begins and does not end until enough information is gathered that allows for sufficient judgment. In cases where social information is based on experts, basing decisions on normative influences can lead to sufficient conclusions.

Attitudinal influence was the basis for behavioral intentions across the seven behaviors used in this study. One explanation for this outcome could be that these behaviors were considered important enough to base behavioral judgments on informational sources rather than normative sources. The sufficiency principle suggests another explanation. Perhaps the study participants initially sought out normative information and found it insufficient to make a behavioral decision, resulting in their attitudinal dependence. The insufficiency of the normative information could be due to a non-obvious expert in relation to the behavioral domain. Experts tend to be influential because novice individuals may assume that the experts behave or think based on reliable information. However, if no experts are visible or available, then social modeling and normative influence may be suppressed. Even if experts were present in the community, the influence of expertise is only possible if the expertise is known. Future study is necessary to test the role of the sufficiency principle in the prediction of informational and normative influence, as the data do not contain information about the sequential process of information seeking.

Behavior Type

The type of behavior may also determine which influence source is used in the formation of a decision. Prior research indicates that variation in weights by behavior type is expected with judgmental or factual decision tasks, and also that behaviors may shape the contributory influence of attitude and subjective norm beyond individual tendencies to normative or attitudinally controlled decision processes (Trafimow & Finlay, 2001b; Trafimow & Davis, 1993). Furthermore, the relative weights may be based on the influence source that provides the most information (Eagly & Chaiken, 1993).

The first research question evaluated whether the weights varied across the seven teaching behaviors used in this study. These test result indicated that the weights did not vary across the teaching behaviors, and that informational influence was the main source used to form behavioral intent. However, the results show that there is a suggestion of variation in attitude weight when a less conservative criterion of .10 is employed. Given the suggestion that weights may vary across the behaviors used in this study, it is expected that more definitive findings will be found with other behaviors, such as attending a departmental picnic or volunteering for faculty senate duties. Future research is needed to explore whether various types of behavior predict the source of influence used in making behavioral decisions, either to contribute scope conditions of the SSI or to derive an alternative explanation for how these sources vary.

Contextual Factors

Features of the context can also influence the relative contribution of attitudinal and normative influence. Structural centrality may have some impact under certain circumstances, but also other network positions can be evaluated. In terms of diffusion of innovations, innovators are individuals who are the first to adopt an innovation and are oftentimes located on the network periphery. Individuals occupying this network position, perhaps defined by a bridging role, may base their decision on attitudinal influence rather than normative influence because there is no normative environment available to influence the behavioral choice for these initial adopters.

Network characteristics can improve prediction of individual behavioral choice. For example, the threshold perspective of normative influence states that individuals will be influenced by social information as the number of individuals who perform the behavior increases (Valente, 1995). This phenomenon represents a consensus principle; persuasion is greater with multiple sources as opposed to a single source. Perhaps the consensus principle did not operate for the individuals included in this study because the teaching behaviors used are not salient or evident to others. The data does not contain information about the salience of the behaviors used in this study, so although this conclusion is suggestive, it is also speculative.

In sum, the speculation about plausible predictors of weights of attitudinal and normative influence remains to be tested. Of the proposed predictors tested within this study (structural centrality, rank, and behavior type), none emerged as a significant predictor. It is proposed that individual differences, features of the behavior, and contextual factors all play a role in the contributory influence of attitude and subjective norm. Developing an account for these multiplicative predictors that are responsible for the contributory influence of attitude and subjective norm will be the basis for a theory of the 'self-other' balance between the sources of influence.

Diffusion Theory

In addition to informing about a structural predictor of contributory influence, learning that attitude weights do not appear to vary by structural centrality holds implications for Diffusion of Innovations Theory. The findings of this study suggest that central individuals must have limited influence when all network members have a heavy weight for their attitude. However, this assumption is questionable because it does not fit with what is known about the influencing role of opinion leadership. Instead, the lack of disparity in attitude weights between central and non-central individuals could suggest that, if influence occurs between these individuals, it does so in ways not captured by the measures used in this study.

Another interpretation is that the diffusion context captured in this study may not contain strong opinion leaders or evident experts on the domain of teaching behaviors. In the absence of influential individuals, the outcome that attitude weights were unvaryingly heavier across all instructors is plausible because the subjective norm measure would not reflect high 'motivation to comply' responses. The data reveal that few individuals possessed high centrality scores (the highest centrality score was .60 on a 0-1 scale, with a mean of .05, SD = .10). Implications for diffusion are that networks may not be developed enough or stable enough to support an opinion leader. In these diffusion contexts, no one in particular emerges as a local expert on the behavioral domain.

In contrast to diffusion environments that consist of more stable networks with highly visible and agreed upon opinion leaders, diffusion processes will in some ways differ when diffusion contexts are underdeveloped. If individuals do not have a particular individual, or local expert, to turn to in regards to teaching behavioral decisions, then no single person can be the catalyst for change. In these circumstances, recommendations for diffusion efforts ought to change from targeting central individuals to creating institutional systems that encourage the emergence of central individuals.

One last interpretation focuses on the type of influence that opinion leaders have over networked others. Rogers suggests that opinion leaders can wield both informational and normative influence (Rogers, 1995). Central individuals may have been influential over others within the social network; they may have wielded informational rather than normative influence. To address this last interpretation, a study would need to capture the type of influence experienced by connected others. One way to measure the type of influence that flows through social ties is an analysis of the content that is exchanged between connected individuals. Future research should focus on teasing out these sources of influence and the relationship between influential people and structural positioning within diffusion contexts.

Limitations and Future Recommendations

Limitations of this study qualify the conclusions drawn from these data. This section reviews these limitations, which include use of a single behavioral domain, measurement of subjective norm, and power of the hypothesis test. Recommendations for future study are provided along with a description of the limitations.

Subjective Norm Measurement

As a starting point, a TRA-inspired measure was used to operationalize subjective norm. This construct was measured as a product of two scores. The first represented the perceived attitude each important other held toward each of seven behaviors and the second represented one's motivation to comply with each important other. This particular measure was selected to represent the perceived normative environment for each individual. However, the measurement of this construct can be improved in future research to accommodate a multi-dimensional definition of normative influence.

The relative influence of attitude as the predominant contributor to behavioral intent is seen in multiple TRA studies (Donald & Cooper, 2001). This is also replicated by the data collected in this study; attitudinal influence significantly predicts behavioral intentions across all seven teaching behaviors. In an effort to explain why subjective norm often does not contribute to behavioral intentions relative to attitudinal influence, scholars suggest an alternative conceptualization of this construct: this alternative specifies multiple components to describe normative environments that include dimensions that lie beyond subjective perceptions (Cialdini, Kallgren, & Reno, 1991; Donald & Cooper, 2001; Green, 1998).

Green (1998) proposed a measure of group normative influence as a substitute to the subjective norm measure proposed within the TRA. Using the Jackson Return Potential Model, group norm is conceptualized as the distribution of approval or disapproval of group members' behaviors and the degree to which a group enacts this behavior. Here, normative influence includes an objective component. The approval or disapproval of a given behavior is averaged across all members, representing an objective assessment of normative influence. Group pressure is expected in situations when group norms are well formed and are intensely held by the group members, creating an environment in which normative sanctions will regulate behaviors. In these situations, Green suggests that the Jackson Return Potential Model can be used in place of the traditional TRA subjective norm measure to capture an objective, rather than a subjective, normative environment. Green's work is useful because it proposes an alternative measure of norms within well-formed groups.

The normative construct is further expanded by Donald and Cooper (2001), who introduce a theory to conceptualize and operationalize the domain of normative influence. Instead of a single variable, normative influence is made up of facets that represent multiple dimensions. Four facets make up the normative domain: (1) personal beliefs, (2) social normative beliefs, (3) behavioral norms, and (4) subjective norms. Personal beliefs indicate what one feels should be done and social normative beliefs indicate what others feel should be done. Behavioral norms, which are in the tradition of Bandura's social learning theory, represent the influence from the observeability of others' behavioral enactment and subjective norms are the perception that others feel that an individual should/should not perform a behavior. Findings show that these multiple categories of normative influence hold discriminate validity and also represent dimensions of normative influence. Consequently, measuring one of these dimensions may provide partial information about the normative environment.

Both Green's work and Donald and Cooper's findings contribute to a growing pool of evidence that supports a multifaceted view of normative influence. This work suggests that future research including a normative influence component should also include a broader set of normative measures to capture this construct, one that represents behavioral, social, and personal norms as well as objective and subjective assessments of the normative influence context.

Measurement of Relative Weights

The second research question inquired about the relationship between self-reports of relative weights and empirically estimated weights. The correlation between these two methods for obtaining relative weighting was non significant. This result indicates that either the self-reported measure did not accurately reflect the empirically derived weights, or that this self-report measure was insufficient to capture this construct. As an alternative, Friedkin and Johnson (1999) use a self-report measure that is proposed to capture perceived relative interpersonal influence. The instructions for this measure are as follows (Friedkin & Johnsen, 1999):

> You have been given a total of 20 poker chips. Each chip represents influence upon your final opinion. Divide the chips into two piles, Pile A and Pile B. Pile A will represent the extent to which the conversations you had with the other persons influenced your final opinion. Pile B will represent the extent to which the conversations you had with the other persons did not influence your final opinion.
>
> Now place Pile B to the side and focus only on Pile A. Consider the extent to which you feel each member of the group influenced your own final opinion. Distribute the chips in Pile A into piles for each of the other members of the group according to how much they influenced your final opinion. (p. 217)

Self-report assessments of interpersonal influence significantly correlated with derived coefficients of normative influence, suggesting that there is potential for a self-report measure for relative weights (Friedkin & Johnsen, 1999). However, this measure captures susceptibility to normative influence only, and the measure does not capture attitudinal influence. Instead, attitudinal influence is derived from this measure of normative influence. Consequently, the measure proposed by Friedkin and Johnsen does not capture the relative contribution of attitude versus subjective norm independently. However, this measure could be altered to reflect a comparison between these two behavioral determinants, and this should be done in future research as an improvement over the single item measure used in this study.

Power

The power estimate for the hypothesis test was moderate, and the design effect calculation suggested that the optimal sample size for this multilevel random-effects model was a sample size of 211 participants, approximately 100 more participants than were included in the study. Also, although the data were aggregated across departments, it is worth noting that power was impacted very little by this aggregation because "power is virtually unaffected when group is the unit of analysis and the intraclass correlation is zero" (Kashy & Kenny, 2000).

Related to the power of the test, the reliability of the centrality scores played a role in determining the study sample size. The sample size for individuals was restricted by departments who reflected response rates that were 30% or greater to ensure that the centrality scores were reliable, according to Costenbader and Valente's (Costenbader & Valente, 2002)findings. As a result of this response rate cut-off, 13 of 26 departments remained in the analysis. Individual responses were represented at the second level of the model, and only those who completed the survey were included in the analysis, resulting in a sample size of 115 respondents.

Efforts were made to increase both samples; however challenges were encountered at each level. At level 1, increasing the number of behaviors would have increased the survey length to intolerable levels, which would have negatively affected the response rates. At level 2, although reminder letters were distributed (along with a roll of Lifesavers candy as an incentive) to emphasize the response rate, some faculty chose not to participate. At level 3, increasing the respondents by adding more departments was also constrained because the sample was limited to departments that contained at least 20 members (with the exception of French, which contained 18). Future tests that use this type of multilevel random-effects model can increase power by increasing the number of behaviors used for the random-effect component, increase the number of respondents at the individual level, or increase the number of networks included in the study.

Future Directions for Communication Network Theory

In their review of research on communication networks, Monge and Contractor (2001) emphasize that future research should include multiple levels of analysis (with the aid of social network analysis) as well as merge multiple theoretical perspectives. This study is an example of such an approach. As a result of this study, many directions for future research have been proposed in this discussion to guide future investigations into influence processes. Three additional research directions can guide this pursuit: Exploring the basis for network ties, developing pragmatic network analysis, and engaging in evolutionary network analysis. All three of these directions reflect a multilevel and multitheoretical perspective.

Basis for Network Ties

Varying the topic used to define social ties could reveal interesting differences in network configuration that may not be revealed by general network approaches. The results of this study indicate that sensitivity to dimensions relevant to a behavioral decision is important when drawing inferences about behavioral choices from network data. For instance, this study included the behavior of using the web to deliver course content. A central person relevant to this decision may not be a fellow instructor but may instead be an individual who is hired to provide technical support for a department. Even if this person were included in the roster list, this individual may not appear within the social network because it is not expected that conversations would focus on teaching. Instead, conversations would more likely focus on technical issues, such as computer resources and Internet connectivity. Although it was not the focus of this investigation to explore the relationship between the basis of the network and network configuration, the discovery that network configurations may vary according to the topical basis used to describe the network is important to consider in future network analyses.

Pragmatic Network Analysis

Interpersonal influence occurs when one individual changes the beliefs, attitudes, or behavior of another individual. This can happen through coercion or compliance, through well-reasoned argument, or through the transfer of information. In all cases, influence occurs at the recipient level. The subject of the influence is motivated to comply with a demand, request, reasoning, or with additional information. Understanding how influence occurs, either through informational or normative sources, can be enriched by examining the content of communication ties. Jacobs and Jackson (1982) propose that discourse analytic methods capture interpersonal influence; dialogue is analyzed to reveal the complex and often subtle influence strategies employed by interlocutors. In addition, interaction has been analyzed in light of how individuals behave in their institutional context (Drew & Heritage, 1992).

The coding of communication ties to capture influence sources exemplifies a pragmatic approach to networks of interpersonal influence. Lewis and Seibold's work illustrates one approach to analyzing the content of communication ties within a decision context. Their work consisted of analyzing innovation-related interactions into content categories relevant to adoption decisions: concerns about an innovation's impact on individual performance, evaluations of normative environments, and uncertainty about sources of information on the innovation impact behavioral outcomes (1993). Their findings suggest that these coping responses are relevant to behavioral outcomes, and in particular, to the adoption of innovations.

In this tradition, analysis of conversations held among individuals engaged in decision-making will reveal useful information about the role of interpersonal influence within larger social structures and within diffusion contexts. A growing trend in social network analysis research is to include analysis of conversational content within social ties, and this method is labeled 'pragmatic network analysis' (Breiger, 2001, in press).

This trend is expected to continue because incorporating analysis of the content of social ties can enrich theories of social networks as well as and diffusion processes.

Evolutionary Network Analysis.

Influence processes are best modeled over time. Diffusion of Innovations Theory and the SSI both predict outcomes based on this variable. The inclusion of time in social network analysis tracks the evolution of not only attitudes and behavior, but also the structure of the network itself. Interest in analyzing network structure from an evolutionary perspective is growing within the social network literature, and analysis methods are becoming increasingly available to researchers interested in the dynamic evolution of network structure over time. In addition, time can inform relationships between macro and micro level variables in multilevel theories. Of interest is the exploration of how conversational content and individual level behavior varies as a result of social structure and, conversely, how conversation or behavior may drive how social structures are configured. The mutual influence between macro and micro levels is illustrated by Burkhardt and Brass (1990), who discovered that individual level behavior resulted in changes in the diffusion context.

Conclusion

This study of social influence offers a multilevel test of influence processes that provides a basis for integrating structural level variables into explanations of individual level behavior. Results indicate that diffusion contexts may be described in terms of their development in addition to their structure, and doubt is introduced about the assumption that attitude weights are determined by structural centrality. Explaining the conditions that shape influence processes has not yet been achieved, and there is a need to apply a multilevel and multitheoretical perspective to the integration of structural, behavioral, and individual behavioral predictors that will ultimately result in a special theory of the self-other balance.

APPENDICIES

APPENDIX A: LIST OF BEHAVIORS

	Behavior
1	Using a listserv or distribution list within a course
2	Using the web to deliver course content
3	Using undergraduate preceptors to assist in teaching a class
4	Using multiple choice formatted exams
5	Making available to students outlines of lecture notes
6	Using computer software to present lecture material in class
7	Sponsoring independent study work for honors students

APPENDIX B: INDIVIDUAL ATTITUDE

The Faculty Network Study

Instructions: Mark next to the word that best represents your perceptions about engaging in the below teaching practices. For instance, if you think that a practice is *useful* to **your** teaching, select the button that lies closest to this word. Please make sure to enter a value for every measure on this page. If you don't know how you feel about performing a behavior, check the middle button to indicate a 'don't know' response. When finished, click on the 'Submit and Go Forward' button.

I think that using a listserv or distribution list within a course is:	**Useless**	C	C	C	C	C	C	C	**Useful**
	Pleasant	C	C	C	C	C	C	C	**Unpleasant**
	Harmful	C	C	C	C	C	C	C	**Beneficial**
	Easy	C	C	C	C	C	C	C	**Difficult**
I think that using the web to deliver course content is:	Useless	C	C	C	C	C	C	C	Useful
	Pleasant	C	C	C	C	C	C	C	Unpleasant
	Harmful	C	C	C	C	C	C	C	Beneficial
	Easy	C	C	C	C	C	C	C	Difficult
I think that using undergraduate preceptors to assist in teaching a class is:	**Useless**	C	C	C	C	C	C	C	**Useful**
	Pleasant	C	C	C	C	C	C	C	**Unpleasant**
	Harmful	C	C	C	C	C	C	C	**Beneficial**
	Easy	C	C	C	C	C	C	C	**Difficult**
I think that multiple choice formatted exams is:	Useless	C	C	C	C	C	C	C	Useful
	Pleasant	C	C	C	C	C	C	C	Unpleasant
	Harmful	C	C	C	C	C	C	C	Beneficial
	Easy	C	C	C	C	C	C	C	Difficult

APPENDIX C: OTHER'S ATTITUDE

The Faculty Network Study

Instructions: For each person you have identified, mark the spot that lies closest to your best guess as to how he or she feels about performing the following behaviors. Please make sure to enter a value for every measure asked for on this page. **If you don't know how to answer a question, check the middle button to indicate a 'don't know' response.** Click on the 'Submit and Go Forward' button when you are finished.

I think that Steven P Mclaughlin thinks that using a listserv or distribution list within a course is:
Favorable ◉ ○ ○ ○ ○ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that using the web to deliver course content is:
Favorable ◉ ○ ○ ○ ○ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that using undergraduate preceptors to assist in teaching a class is:
Favorable ○ ○ ○ ◉ ○ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that using multiple choice formatted exams is:
Favorable ○ ○ ○ ○ ◉ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that making available to students outlines of lecture notes is:
Favorable ○ ○ ◉ ○ ○ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that using computer software to present lecture material in class is
Favorable ○ ◉ ○ ○ ○ ○ ○ Unfavorable

I think that Steven P Mclaughlin thinks that sponsoring independent study work for honors students is:
Favorable ◉ ○ ○ ○ ○ ○ ○ Unfavorable

1 of 3 Pages

APPENDIX D: MOTIVATION TO COMPLY

The Faculty Network Study

Instructions: For each of the following statements, mark the spot that lies closest to how you feel about the likelihood of the statement. **If a statement is not relevant to you, check the middle button to indicate a 'not applicable' response.** Click on the 'Submit and Go Forward' button when you are finished with this page.

In regards to teaching behaviors in general, I want to do as Steven P Mclaughlin does.
LIKELY ◉ ○ ○ ○ ○ ○ ○ **UNLIKELY**

In regards to teaching behaviors in general, I want to do as Stuart E Marsh does.
LIKELY ○ ○ ○ ◉ ○ ○ ○ UNLIKELY

In regards to teaching behaviors in general, I want to do as Wayne E Coates does.
LIKELY ○ ○ ○ ○ ○ ○ ○ **UNLIKELY**

[redacted]

Exit Survey Contact Stacy

APPENDIX E: BEHAVIORAL INTENT

The Faculty Network Study

Instructions: Indicate whether or not you intend to perform each behavior by making a mark next to the word that best represents your response. Please make sure to enter a value for every measure on this page. If you don't know how you feel about performing a behavior, check the middle button to indicate a 'don't know' response. Click on the 'Submit and Go Forward' button when you are finished.

I intend to use a listserv or distribution list within my course(s) during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to use the web to deliver my course content during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to use undergraduate preceptors to assist in teaching my class(es) during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to use multiple choice formatted exams during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to make available to students outlines of my lecture notes for one or more courses during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to use computer software to present lecture material in my class(es) during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

I intend to sponsor independent study work for one or more honors students during the Spring 2002 term.
LIKELY ○ ○ ○ ○ ○ ○ ○ UNLIKELY

APPENDIX F: INITIAL SOLICITATION LETTER

Dear [faculty],

A study is being conducted this semester to test a new theory that has the potential to impact research foci for multiple disciplines within the social sciences. Theoretical work will progress with your help by spending approximately 15 to 20 minutes to respond to a WEB survey. Also, by inquiring about general teaching behaviors, your responses will motivate further study into the teaching resources used by UA faculty with the goal of continually improving instructional support.

[name], department head of [department] has given me permission to contact you personally, and you are chosen because you are a faculty member within this department, one of many included in the study.

Dr. Sally Jackson, Vice Provost for Educational Technology, and Dr. Joseph Bonito, Communication Professor are supervising this study for the dissertation work of Stacy Wolski, Ph.D. Candidate in Communication and project administrator for the Office of Distributed Learning.

To access the survey, please enter this URL into your WEB browser: http://www.teach.arizona.edu between now and Saturday, September 29th. After you respond to the permission form, you will be asked for your login and password information, which is provided here:

Login: Loginname
Password: password.

Confidentiality of your information is highly valued and will be maintained. If you have any questions about this study you may contact Stacy Wolski at stacy@u.arizona.edu or by phone 626-3729 or 240-2862. You may also contact the Human Subjects Committee office at 626-6721.

Thank you for your consideration; your responses will be a substantial help.

Stacy Wolski
Office of Distributed Learning
Ph.D. Candidate, Department of Communication
The University of Arizona

APPENDIX G: SAMPLE REMINDER LETTER

10/15/2001

Dear Professor [ ],

So far the survey responses and comments provided by the Aerospace and Mechanical Engineering faculty have been very helpful, and I would like to offer my thanks if you have recently completed the survey.

However, there remains a number of faculty who have not participated. If you have not yet visited the survey page at *http://www.teach.arizona.edu/*, I hope that you will find time to do so before this Friday, October 19th. The success of my study lies on the contributions of you and your fellow faculty and I sincerely appreciate your participation!

As a reminder, you will need to enter your unique login and password information:

Login: login
Password: password

Please contact me at stacy@U.arizona.edu or at 626-3729 if you have any questions or comments. Thank you for your help.

Stacy Wolski
Ph.D. Candidate, Department of Communication
Project Administrator, Office of Distributed Learning
The University of Arizona

Table 1: Attitude Weight as a Function of Indegree and Mean Indegree

	Mean Indegree				
Individual Indegree	2	4	6	8	10
0	0.009	0.000	0.000	0.000	0.000
2	0.061	0.001	0.000	0.000	0.000
4	0.293	0.009	0.000	0.000	0.000
6	0.655	0.061	0.001	0.000	0.000
8	0.866	0.293	0.009	0.000	0.000
10	0.950	0.655	0.061	0.001	0.000
12	0.982	0.866	0.293	0.009	0.000
14	0.993	0.950	0.655	0.061	0.001
16	0.998	0.982	0.866	0.293	0.009
18	0.999	0.993	0.950	0.655	0.061
20	1.000	0.998	0.982	0.866	0.293

Note. from Friedkin (1998).

Table 2: Respondents Per Department by Rank

Department	Adjunct	Assistant	Associate	Full	Total N
1	1	3	1	4	9
2	2	3	4	3	12
3	1	2	2	3	8
4	2	3	2	7	14
5	1	2	2	4	9
6	2	2	0	1	5
7	1	1	5	3	10
8	5	4	2	2	13
9	2	3	0	3	8
10	1	2	2	4	9
11	3	0	3	1	7
12	1	0	1	2	4
13	1	1	3	2	7
Total	23	26	27	39	115

Table 3: List of All Departments Included in the Selection Pool

Department	Total Number Faculty	Agree to Participate
Accounting*	21	Yes
Aerospace & Mechanical Engineering	41	Yes
Anthropology	35	Yes
Architecture	21	No
Art	58	Yes
Astronomy	42	Yes
Biochemistry	30	No
Chemistry	42	Yes
Computer Science	20	Yes
Ecology & Evolutionary Biology	19	No
Economics	29	Yes
Electrical & Computer Engineering	40	No
English	92	No
French & Italian*	16	Yes
Geosciences	54	Yes
History	30	Yes
Mathematics	90	No
Molecular & Cellular Biology	25	No
Music	42	No
Nursing	51	Yes
Optical Sciences	60	Yes
Physics	38	Yes
Physiology	28	Yes
Plant Science*	20	Yes
Political Science	32	Yes
Spanish & Portuguese	24	Yes
Special Education	19	No
Speech & Hearing Science	27	Yes
Teaching & Teacher Education	30	Yes

Note. * indicates departments used in pilot analysis.

Table 4: Departments Included in Study with Response Rates

Department	Total Faculty	Total Faculty Response	Response Rate
Accounting	21	5	24%
AME	41	10	24%
Anthropology*	35	13	37%
Art*	58	18	31%
Astronomy*	42	13	31%
Chemistry*	42	17	40%
Computer Science*	20	13	65%
Economics	29	4	14%
French*	16	7	44%
Geosciences	54	11	20%
History*	30	14	47%
Nursing*	51	16	31%
Optical Sciences	60	8	13%
Physics*	38	19	50%
Physiology*	28	15	54%
Plant Science*	20	10	50%
Political Science*	32	18	56%
Spanish	24	7	29%
Speech and Hearing*	27	10	37%
Teaching and Teacher Education	30	6	20%

Note. Departments with response rates grater than 30% were retained in the analysis, and are identified by the *.

Table 5: Descriptive Information on Departments Included in Study

Department	Total Responses to Network Measure	Total Responses to Complete Survey	Response Rate For Complete Survey Per Department
1	13	9	69%
2	18	12	67%
3	13	8	62%
4	17	14	82%
5	13	9	69%
6	7	5	71%
7	14	10	71%
8	16	13	81%
9	19	8	42%
10	15	9	60%
11	10	7	70%
12	18	4	22%
13	10	7	70%

Table 6: Attitude Scale Reliability for Each Behavior – Pilot and Main Study

Behavior	Pilot (N = 20)	Main (N = 115)
1	.73	.78
2	.87	.82
3	.93	.88
4	.55	.71
5	.87	.84
6	.85	.83
7	.72	.79

Table 7: Descriptive Statistics for Attitude, Subjective Norm, Behavioral Intent, and the Empirical Bayes Estimates for Attitude and Subjective Norm

Variable	Minimum	Maximum	M	SD	Variance
Attitude*	-3	+3	1.03	1.52	
Subjective Norm	-90	72	-9.64	19.81	
Behavioral Intent	1	7	4.09	2.64	
Attitude Estimate**	.153	.654	.55	.07	.006
Subjective Norm Estimate	-.596	.258	-.09	.12	.015

Note. * N = 805; ** N = 115. Descriptive information for Attitude, Subjective Norm, and Behavioral Intent are based on responses from 115 individuals on each of seven behaviors (N = 805). Empirical Bayes estimates for attitude and subjective norm were based on 115 individuals.

Table 8: Summary of Fixed Variation Regression Analysis

Variable	*B*	*SE B*	Z	*p*
Attitude	.540	.033	16.616	.000
Subjective Norm	-.038	.033	-1.172	.241
Residual Variance	.688	.034	20.062	.000

Note. Log L = -991.815, N = 115.

Table 9: Summary of Random Variation Regression Analysis

Variable	*B*	*SE B*	*Z*	*p*
Attitude	.544	.037	14.701	.000
Subjective Norm	-.054	.047	-1.146	.252
Attitude Variance	.029	.019	1.547	.061
Subjective Norm Variance	.062	.027	2.324	.010
Attitude and Subjective Norm Covariance	.021	.020	1.076	.282

Note. Log L =-980.440, N = 115.

Table 10: Fixed and Random Model Comparison Results

Model	Parameters	Log	Deviance	Difference χ^2	p
Fixed	2	-991.815	1983.63	22.75	< .05
Random	5	-980.440	1960.88		

Note. The deviance is –2 times the value of the log likelihood function, N = 115, df = 3.

Table 11: Unstructured Covariation Matrix

Behavior	1	2	3	4	5	6	7
1	.668	-	-	-	-	-	-
2	.258	.695	-	-	-	-	-
3	-.060	-.048	.821	-	-	-	-
4	.074	.191	-.015	.639	-	-	-
5	.149	.253	-.172	.146	.538	-	-
6	.145	.247	.045	.235	.241	.637	-
7	.021	-.060	.184	.013	.018	.063	.697

Table 12: Heterogeneous Covariation Matrix

Behavior	1	2	3	4	5	6	7
1	.657	-	-	-	-	-	-
2	.121	.620	-	-	-	-	-
3	.121	.121	1.043	-	-	-	-
4	.121	.121	.121	.635	-	-	-
5	.121	.121	.121	.121	.492	-	-
6	.121	.121	.121	.121	.121	.550	-
7	.121	.121	.121	.121	.121	.121	.842

Table 13: Homogeneous Covariance Matrix

Behavior	1	2	3	4	5	6	7
1	.671	-	-	-	-	-	-
2	.094	.671	-	-	-	-	-
3	.094	.094	.671	-	-	-	-
4	.094	.094	.094	.671	-	-	-
5	.094	.094	.094	.094	.671	-	-
6	.094	.094	.094	.094	.094	.671	-
7	.094	.094	.094	.094	.094	.099	.671

Table 14: Model Comparison Results for Correlation Structures

Model	Parameter	Deviance	$\chi 2$	*df*	*p*
1. Unrestricted δ^2	33	1838.13			
2. Homogeneous δ^2	7	1929.59			
Model 1 & Model 2 Difference			91.47	26	.000
3. Heterogeneous δ^2	13	1908.43			
Model 1 & Model 3 Difference			70.30	20	.000
Model 2 & Model 3 Difference			21.16	6	.002

Table 15: Analysis of Variance for Centrality by Department

Source	SS	*df*	MS	F	*p*
Between Groups (G)	0.131	12.000	0.011	1.21	0.29
Within Groups (S/G)	0.923	102.000	0.009		
Total	1.054	114.000			

Table 16: Analysis of Variance for Attitude Weight by Department

Source	SS	*df*	MS	F	*p*
Between Groups (G)	0.012	12.000	0.001	0.17	0.999
Within Groups (S/G)	0.620	102.000	0.006		
Total	0.633	114.000			

Table 17: Pooled Attitude, Norm, and Intent Descriptives for Each Behavior

	Attitude		Subjective Norm		Intent	
Behavior	M	SD	M	SD	M	SD
1	1.23	1.17	-9.64	19.82	4.70	2.51
2	1.59	1.19	-12.31	19.06	5.00	2.49
3	.49	1.31	-13.45	19.52	1.86	1.72
4	-.39	1.55	-4.98	15.23	3.03	2.60
5	.88	1.60	1.77	20.57	4.76	2.57
6	1.35	1.35	-11.22	17.59	4.75	2.52
7	2.09	1.08	-12.07	18.92	4.58	2.36

Note. N = 115.

Table 18: Pooled Descriptives for Centrality and the Empirical Bayes Estimates for Attitude and Subjective Norm

Variable	M	SD
Centrality	.05	.10
Empirical Bayes Attitude Weight	.55	.07
Empirical Bayes Subjective Norm Weight	-.09	.12

Note. N = 115.

Table 19: Attitude Descriptives for Each Behavior by Department

	Behavior 1		Behavior 2		Behavior 3		Behavior 4	
Department	M	SD	M	SD	M	SD	M	SD
1	.78	1.70	1.44	1.30	.44	1.51	1.07	.80
2	1.50	1.67	1.53	1.78	.44	1.48	-1.7	1.71
3	1.42	.83	1.58	.85	.42	1.67	.54	.83
4	1.17	.93	1.69	1.08	.93	1.08	-1.4	.92
5	1.63	.59	2.04	1.03	1.67	1.14	-1.5	1.29
6	1.07	1.48	2.00	.85	.40	.89	-1.4	1.16
7	1.17	1.41	1.80	1.10	-.43	1.18	-1.3	1.58
8	1.38	1.10	1.41	1.16	.31	.96	.62	1.35
9	1.08	.53	1.29	.97	-.04	.68	-.67	1.13
10	1.74	.85	2.22	.99	.59	1.43	.48	1.40
11	.86	1.07	.52	1.27	.43	1.20	.19	.60
12	.42	1.83	1.83	1.45	.25	2.75	-.42	1.48
13	1.05	1.10	1.38	.97	.67	.88	.19	2.12

Table 19: Attitude Descriptives for Each Behavior by Department -- *Continued*

	Behavior 5		Behavior 6		Behavior 7	
Department	M	SD	M	SD	M	SD
1	-.30	1.81	1.07	1.72	2.26	.95
2	.36	1.57	.94	1.36	2.44	1.18
3	.08	1.28	1.50	.96	2.08	1.02
4	.57	1.44	.83	.99	2.04	1.26
5	1.81	.67	.93	1.80	1.93	1.06
6	.60	1.74	.93	1.63	1.80	1.30
7	1.03	1.75	1.20	1.56	2.47	.71
8	1.05	1.63	2.26	.86	2.28	.93
9	1.42	1.50	.58	1.24	2.00	1.04
10	2.11	1.12	2.04	1.16	2.48	.58
11	-.05	1.81	.76	1.05	.71	.78
12	.67	1.61	2.41	1.17	1.17	1.69
13	2.10	.81	2.57	.63	2.33	1.11

Table 20: Norm Descriptives for Each Behavior by Department

	Behavior 1		Behavior 2		Behavior 3		Behavior 4	
Department	M	SD	M	SD	M	SD	M	SD
1	-26.11	27.93	-24.78	28.53	-12.56	17.11	-13.78	26.36
2	-8.5	17.09	-9.58	18.51	-4.50	12.16	5.75	18.85
3	-10.88	16.23	-14.87	21.54	-9.75	12.38	-1.00	12.75
4	-1.57	8.77	-2.07	8.75	-.64	10.65	.86	8.34
5	-16.89	21.99	-20.0	16.49	-12.89	10.28	14.56	17.74
6	-17.40	20.53	-18.20	20.39	-10.00	14.07	14.00	16.60
7	-19.30	24.98	-18.90	22.86	-3.20	28.89	20.20	27.46
8	-17.38	22.10	-13.54	16.06	-7.31	9.44	-6.23	15.01
9	-1.13	6.22	-10.38	26.29	10.50	24.48	17.38	21.97
10	-11.33	12.62	-13.67	15.42	-5.89	9.02	-8.11	14.53
11	-4.57	8.14	-3.43	9.14	-5.43	11.69	-4.57	10.13
12	-4.00	8.00	-3.50	7.00	2.00	4.00	-1.50	3.00
13	-21.86	22.15	-25.86	24.69	-3.86	7.63	-13.71	27.65

Table 20: Norm Descriptives for Each Behavior by Department -- *Continued*

	Behavior 5		Behavior 6		Behavior 7	
Department	M	SD	M	SD	M	SD
1	-17.33	25.73	-23.11	28.95	-29.56	35.08
2	-4.67	12.26	-4.33	11.72	-13.0	22.52
3	-8.13	13.2	-15.0	18.37	-7.87	11.51
4	-2.86	7.83	-.29	7.83	-1.57	10.74
5	-13.11	15.50	-14.0	19.34	-20.11	13.98
6	-5.40	14.79	-7.20	23.61	-26.20	30.10
7	-11.80	15.59	-14.50	15.81	-14.60	15.31
8	-15.23	19.66	-17.54	19.11	-18.62	20.67
9	-9.88	25.80	-3.00	10.82	-10.88	29.08
10	-19.44	17.61	-18.89	17.78	-20.44	16.87
11	-3.71	8.18	-3.57	9.24	-4.86	11.50
12	-3.50	7.00	-4.50	9.00	2.00	4.00
13	-31.14	24.90	-33.14	26.17	-35.57	25.25

Table 21: Intent Descriptives for Each Behavior by Department

	Behavior 1		Behavior 2		Behavior 3		Behavior 4	
Department	M	SD	M	SD	M	SD	M	SD
1	3.89	2.80	4.22	2.91	1.44	1.01	5.44	2.60
2	5.33	2.27	4.67	2.57	2.67	2.31	1.50	1.00
3	5.38	1.60	5.62	2.00	3.13	2.95	4.13	2.90
4	4.42	2.68	4.79	2.48	1.50	1.09	1.29	.61
5	6.00	2.00	6.44	1.67	2.11	2.09	1.56	1.33
6	5.80	2.68	6.20	1.79	2.20	2.68	1.20	.45
7	2.80	2.70	5.10	2.84	1.60	1.26	2.00	2.16
8	5.38	2.40	4.69	2.43	1.46	.97	4.77	2.95
9	3.75	2.55	4.13	2.70	1.50	1.41	1.50	1.41
10	5.56	2.01	6.44	1.33	1.78	1.56	5.89	2.09
11	4.29	3.09	3.71	3.09	2.43	2.30	3.43	3.05
12	4.00	2.58	5.50	3.00	1.00	0.00	3.00	2.82
13	4.29	2.56	4.14	2.85	1.29	.49	3.86	2.48

Table 21: Intent Descriptives for Each Behavior by Department -- *Continued*

	Behavior 5		Behavior 6		Behavior 7	
Department	M	SD	M	SD	M	SD
1	3.67	2.78	4.67	2.92	4.33	2.78
2	2.91	2.54	3.67	2.90	5.75	1.76
3	5.00	2.07	5.50	1.77	3.88	1.36
4	3.79	2.52	3.07	2.09	4.79	2.72
5	5.89	1.90	4.89	2.71	3.89	2.67
6	4.20	3.03	3.60	3.13	4.20	2.77
7	4.10	3.07	3.50	2.88	4.40	2.59
8	5.54	2.60	6.92	.28	4.77	2.49
9	5.13	2.64	4.50	2.14	4.63	2.56
10	6.33	1.32	5.56	2.19	4.44	1.81
11	4.71	2.75	3.71	2.56	4.00	2.71
12	5.00	2.82	6.5	.58	3.00	2.82
13	6.86	.38	6.85	.38	6.00	1.41

Table 22: Centrality Scores and Attitude Weights for Respondents by Department

Department	Respondents	Centrality Scores	Attitude Weight
1	1	0.006	0.495
	2	0.002	0.582
	3	0.113	0.648
	4	0.017	0.521
	5	0.113	0.533
	6	0.045	0.576
	7	0.000	0.369
	8	0.006	0.630
	9	0.017	0.566
2	1	0.024	0.635
	2	0.062	0.613
	3	0.151	0.547
	4	0.024	0.521
	5	0.024	0.405
	6	0.009	0.505
	7	0.151	0.563
	8	0.009	0.598
	9	0.009	0.591
	10	0.000	0.449
	11	0.003	0.549
	12	0.003	0.612
3	1	0.153	0.586
	2	0.062	0.583
	3	0.062	0.608
	4	0.153	0.561
	5	0.024	0.566
	6	0.153	0.593
	7	0.000	0.574
	8	0.062	0.411

Table 22: Centrality Scores and Attitude Weights for Respondents by Department -- *Continued*

Department	Respondents	Centrality Score	Attitude Weight
4	1	0.000	0.612
	2	0.476	0.584
	3	0.110	0.562
	4	0.000	0.548
	5	0.016	0.603
	6	0.110	0.558
	7	0.002	0.651
	8	0.043	0.437
	9	0.043	0.474
	10	0.043	0.495
	11	0.000	0.604
	12	0.043	0.587
	13	0.016	0.376
	14	0.001	0.485
5	1	0.043	0.512
	2	0.000	0.597
	3	0.110	0.548
	4	0.006	0.592
	5	0.002	0.468
	6	0.016	0.513
	7	0.000	0.634
	8	0.002	0.505
	9	0.006	0.573
6	1	0.008	0.501
	2	0.145	0.586
	3	0.059	0.579
	4	0.059	0.456
	5	0.022	0.510

Table 22: Centrality Scores and Attitude Weights for Respondents by Department -- *Continued*

Department	Respondents	Centrality	Attitude Weight
7	1	0.010	0.599
	2	0.004	0.500
	3	0.000	0.529
	4	0.000	0.586
	5	0.010	0.540
	6	0.001	0.652
	7	0.001	0.153
	8	0.004	0.603
	9	0.001	0.568
	10	0.010	0.614
8	1	0.000	0.580
	2	0.339	0.537
	3	0.025	0.557
	4	0.065	0.588
	5	0.065	0.569
	6	0.339	0.494
	7	0.065	0.465
	8	0.009	0.642
	9	0.003	0.418
	10	0.065	0.563
	11	0.003	0.651
	12	0.003	0.637
	13	0.009	0.617
9	1	0.071	0.616
	2	0.004	0.589
	3	0.001	0.511
	4	0.071	0.553
	5	0.071	0.553
	6	0.001	0.634
	7	0.604	0.517
	8	0.071	0.522

Table 22: Centrality Scores and Attitude Weights for Respondents by Department -- *Continued*

Department	Respondents	Centrality	Attitude Weight
10	1	0.000	0.531
	2	0.058	0.612
	3	0.000	0.567
	4	0.003	0.477
	5	0.000	0.567
	6	0.003	0.548
	7	0.003	0.579
	8	0.001	0.524
	9	0.003	0.407
11	1	0.101	0.520
	2	0.040	0.569
	3	0.101	0.591
	4	0.040	0.581
	5	0.040	0.413
	6	0.453	0.536
	7	0.040	0.588
12	1	0.107	0.577
	2	0.001	0.468
	3	0.002	0.506
	4	0.016	0.621
13	1	0.164	0.589
	2	0.004	0.365
	3	0.010	0.651
	4	0.067	0.545
	5	0.026	0.603
	6	0.026	0.545
	7	0.004	0.510

Table 23: Correlations between Attitude Weight and Centrality Scores by Department

Department	N	Pearson Product-Moment *r*
1	9	.374
2	12	.103
3	8	.160
4	14	.125
5	9	-.140
6	5	.599
7	10	.222
8	13	-.350
9	8	-.413
10	9	.442
11	7	-.023
12	4	.448
13	7	.293
Average Correlation		.142

Note: No correlations are significant at the $\alpha = .05$ level.

Table 24: Descriptives for Centrality and Attitude Weights by Department

	Centrality		Attitude Weight	
Department	M	SD	M	SD
1	0.036	0.046	0.547	0.083
2	0.039	0.055	0.549	0.070
3	0.084	0.061	0.560	0.062
4	0.065	0.124	0.541	0.077
5	0.021	0.036	0.549	0.054
6	0.058	0.053	0.526	0.055
7	0.004	0.004	0.534	0.141
8	0.076	0.120	0.563	0.070
9	0.112	0.202	0.562	0.047
10	0.008	0.019	0.535	0.061
11	0.116	0.151	0.543	0.063
12	0.032	0.051	0.543	0.069
13	0.043	0.058	0.544	0.091

Table 25: Summary of Regression Analysis for Centrality Predicting Attitude Weight

Variable	*B*	*SE B*	T	*p*
Attitude	.556	.029	19.17	.00*
Subjective Norm	-.049	.035	-1.40	.16
Attitude * Centrality	.022	.029	.76	.45

Note. Log Likelihood = -980.424, *df*=113, * = $p < .05$.

Table 26: Model Comparison between TRA and SSI

Model	Parameters	Log	Deviance	Difference χ^2	p
TRA	5	-980.440	1960.88	.03	< .05
Attitude* Centrality	6	-980.424	-1960.85		

Note. The deviance is –2 times the value of the log likelihood function, $df = 1$.

Table 27: Summary of Regression Analysis for Behavior*Attitude and Behavior* Subjective Norm

Variable	Estimate	SE	Z	*p*
Attitude	.667	.079	8.384	.00*
Subjective Norm	-.063	.076	-0.834	.40
Attitude * Behavior	-.029	.017	-1.698	.09
Subjective Norm * Behavior	.002	.015	0.119	.91

Note: Log Likelihood = -978.752, * = $p < .05$, N = 115.

Table 28: Summary of Regression Analysis for Each Behavior

	Variable	*B*	T	*p*
Behavior 1				
	Attitude	.51	6.31	.00
	Subjective Norm	-.04	-.54	.59
Behavior 2				
	Attitude	.49	5.53	.00
	Subjective Norm	.07	.76	.45
Behavior 3				
	Attitude	.32	3.32	.001
	Subjective Norm	-.04	-.46	.644
Behavior 4				
	Attitude	.53	5.77	.00
	Subjective Norm	-.08	-.87	.39
Behavior 5				
	Attitude	.69	9.7	.00
	Subjective Norm	-.09	-1.2	.22
Behavior 6				
	Attitude	.54	6.14	.00
	Subjective Norm	-.02	-.24	.81
Behavior 7				
	Attitude	.40	4.32	.00
	Subjective Norm	.02	.16	.87

Note. $df = 114$.

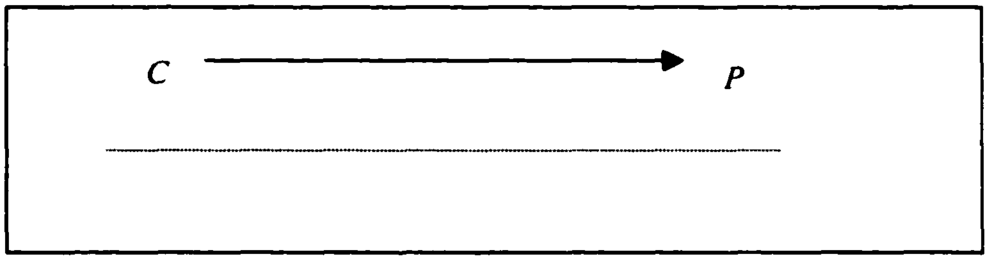
Table 29: Summary of Regression Analysis for Rank*Attitude and Rank* Subjective Norm

Variable	*B*	SE B	T	*p*
Intercept	-.115	.037	-3.01	.00
Attitude	.554	.061	9.00	.00
Subjective Norm	-.020	.078	-.26	.80
Attitude * Rank	.002	.021	.07	.94
Subjective Norm * Rank	-.011	.025	-.42	.67

Note. Results based on unrestricted correlation matrix, $df = 113$.

FIGURES

Figure 1: Macro-Unit Proposition



Note. A dotted line separates the levels; micro-units are placed below the line and macro-units are placed above the line (Snijders & Bosker, 2000). Macro unit variables are denoted by C and by P.

Figure 2: Micro-Unit Proposition

$$a \longrightarrow i$$

Note. The micro-unit variables are denoted by *a* and *i*.

Figure 3a: Macro-Unit Predicting a Micro Unit

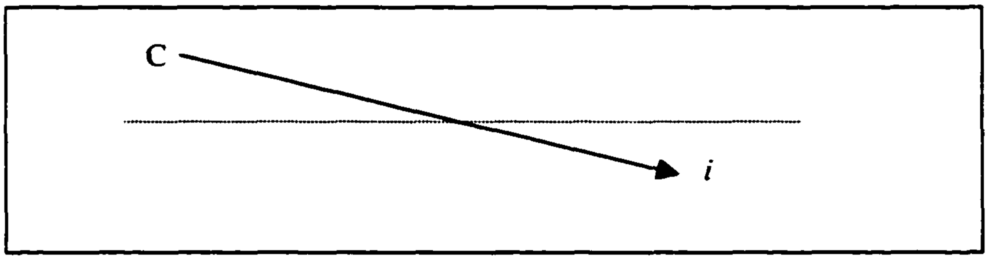


Figure 3b: Macro-Unit Predicting a Micro Unit Controlling for *a*

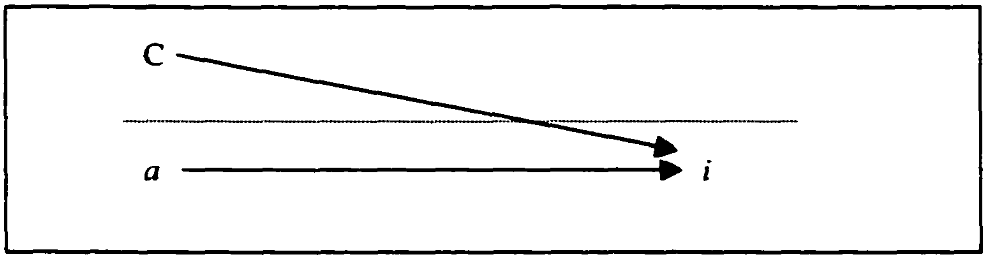


Figure 3c: Cross-Level Proposition

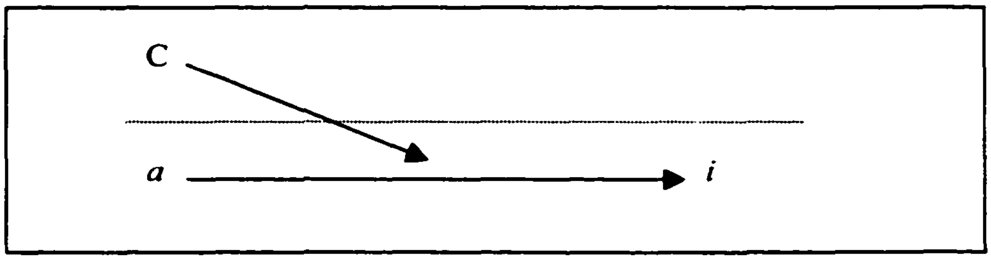


Figure 4: Multilevel Model Specification

Level	Unit	Variable	Effect
3	Departmental	Centrality_a	Fixed
2	Individual	Attitude, Subjective Norm, Intent_b	Fixed
1	Observational	Behaviors 1 - 7	Random

Note. a = scores derived from departmental information; b = scores based on multiple observations from level 1.

Figure 5: Cross-Level Interaction in Random-Effects Model

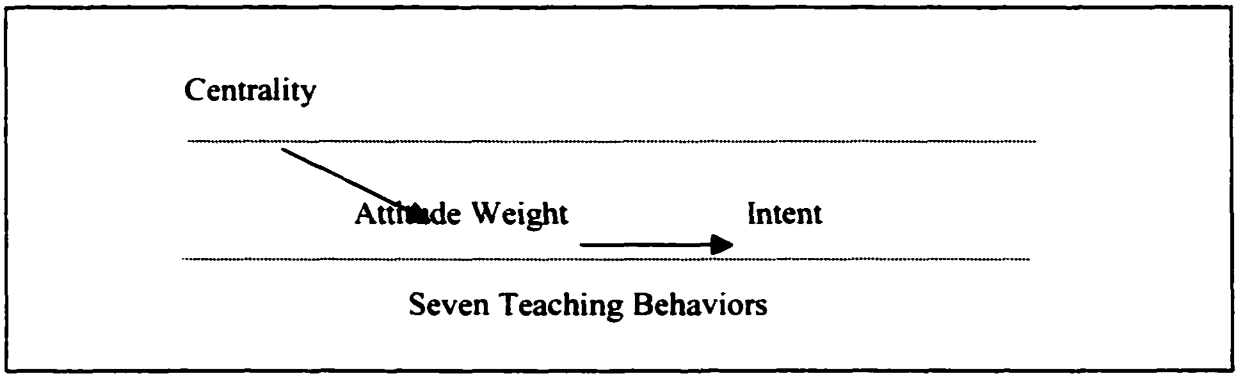


Figure 6: Scatter Plot of Attitude Weights by Centrality

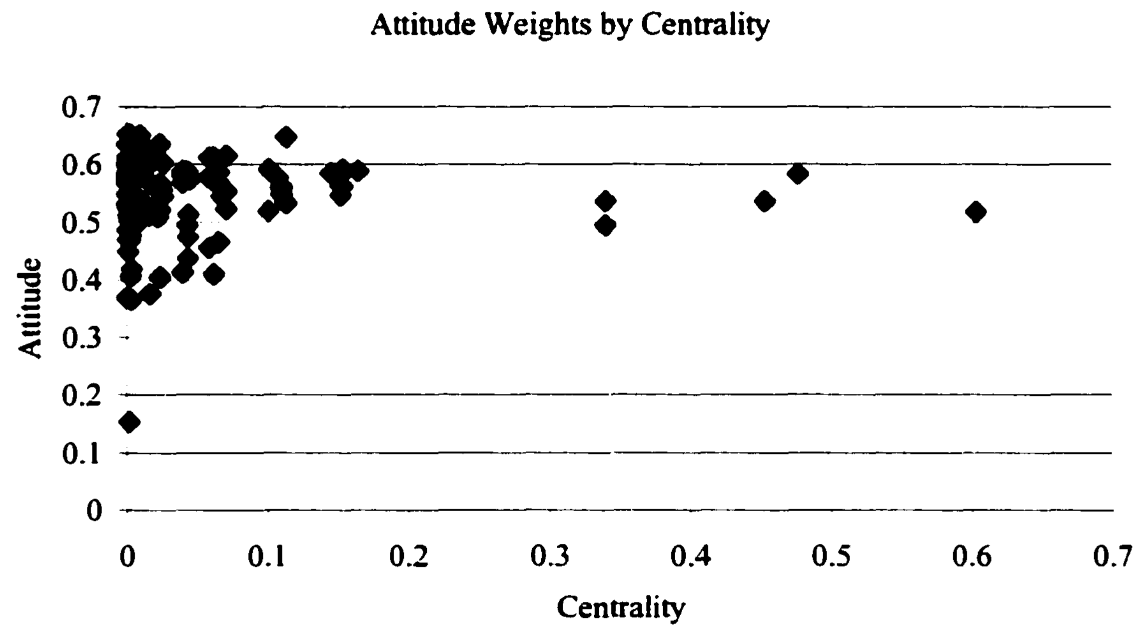


Figure 7: Scatter Plot of Subjective Norm Weights by Centrality

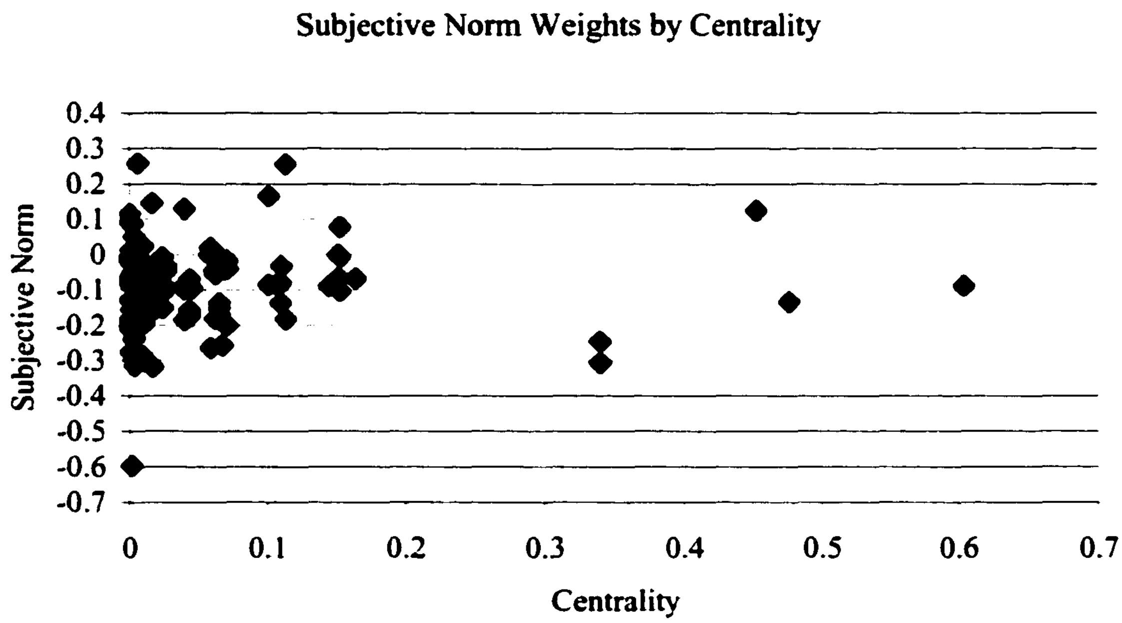


Figure 8: Expected Versus Obtained Attitude Weights by Centrality

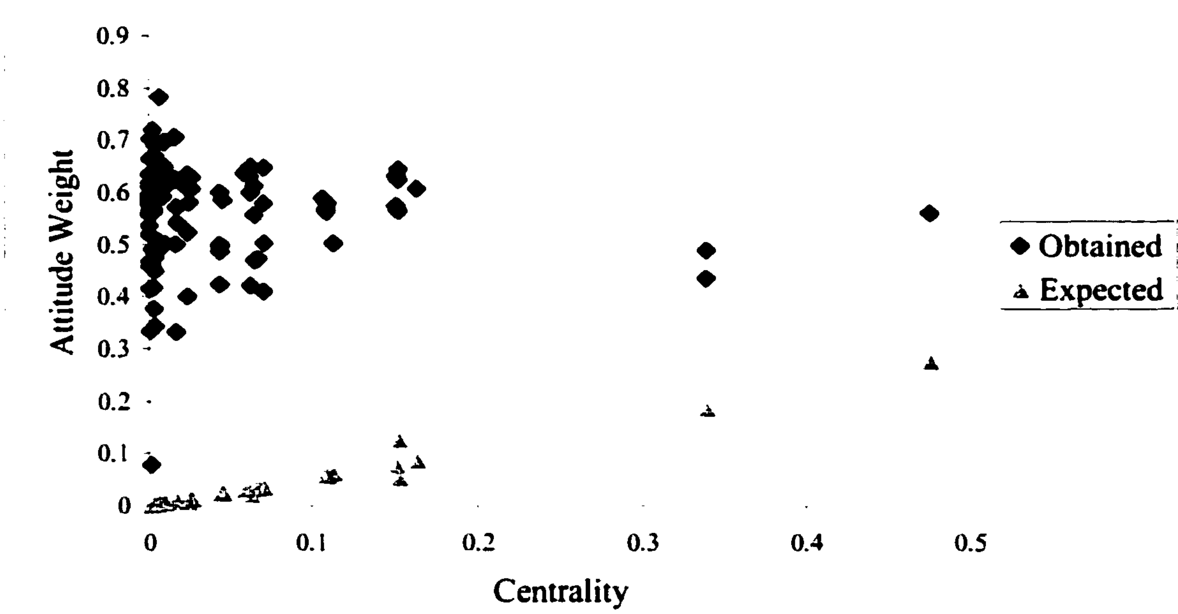
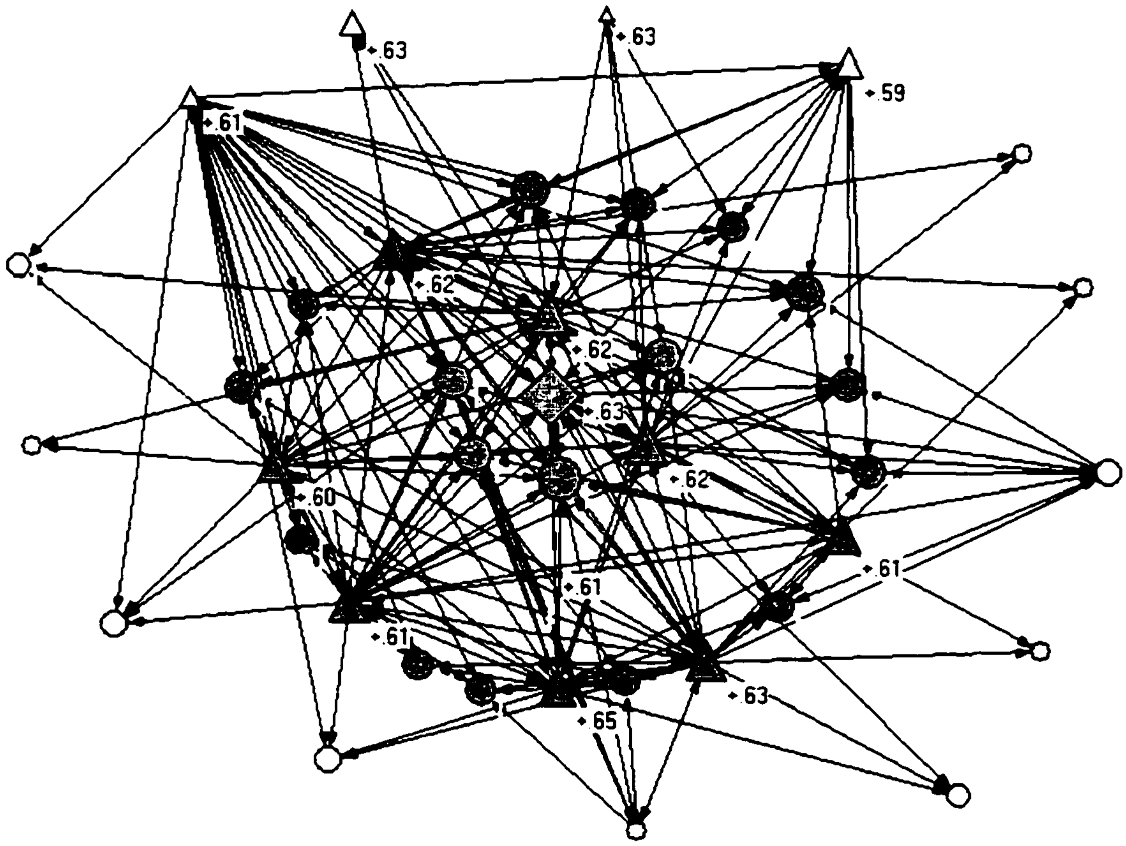


Figure 9: Example Teaching Network with Relative Attitude Weights



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