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Expert decision support system use, disuse, and misuse: a study using the theory of planned behavior

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Abstract

Researchers in the past decade have been actively investigating technology use and disuse among conventional and communications technologies. However, recent advancements in expert systems technology has led to new questions about technology use. Where communications technology, such as e-mail or group collaboration software, facilitates co-evolution of problem solving and decision making among people, expert systems create a transaction between user and computer where ultimately, the computer generates the recommended courses of action. This also differs from conventional decision support tools that merely gather information to inform a human decision maker.

This empirical study used theory of planned behavior to formulate hypotheses about the use, disuse, and misuse of an expert system decision support (EDSS) technology. It was found that EDSS use was negatively related to errors, whereas misuse of EDSS was positively related to errors. More positive attitudes and social influences led to increased EDSS use, while perceptions of control had no apparent effect. The interaction of social influences and attitudes had a significant non-linear relationship with EDSS misuse.

Keywords: Expert systems; Technology use; Theory of planned behavior

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1. Introduction

As expenditures on information systems technology continues to increase concurrent with increasing information systems capabilities, practitioners and researchers are striving to better understand how to maximize the benefits that these technologies offer. Because of their increasing complexity, information technology use/non-use is being actively researched. However, as information systems technology becomes more sophisticated, there are growing opportunities for users to ignore or misuse their intended application.

Previous empirical research has identified relationships among attitudes, perceptions, social influences, and information systems technology use (e.g. Bagozzi, Davis, & Warshaw, 1992; Morris & Venkatesh, 2000; Thatcher & Perrewe, 2002), although this research has largely concentrated on conventional applications such as word processing (c.f. Davis, Bagozzi, & Warshaw, 1992; Klein, Conn, & Sorra, 2001), or communications technology such as e-mail, video teleconferencing, computer-mediated communications, and groupware (c.f. Dennis & Garfield, 2003; Kraut, Rice, Cool, & Fish, 1998; Walsham, 2002). The natures of these technologies introduce a variety of human–computer and interpersonal factors involved in technology use (DeSanctis & Poole, 1994; Roberts & Henderson, 2000).

Recent advancements in expert systems technology, however, have established a new collaborative interchange (Gregor & Benbasat, 1999). Where communications technology facilitates interchange among people, the transaction with expert systems is between person and computer; and where conventional applications respond with information from user requests, expert systems not only provide information, but also suggest or make recommendations (Christie & Wu, 2002; Marquardt, 1993). They create an intensive human–computer interaction that evolves through a series of stages – a usage paradigm – to perform complex analyses and derive computer-generated solutions to problems. This intensive exchange tends to elevate anthropomorphic characterization of expert systems and users are sometimes be lulled into forgetting that expert systems are inanimate (Christie & Wu, 2002; Gates, 1995; Gregor & Benbasat, 1999; Marquardt, 1993; Marsh, 1995).

While expert systems are found in a wide variety of applications from strategy development to computer problem analysis (Christie & Wu, 2002; Coulson-Thomas, 1992; Marquardt, 1993; Schoemaker, 1993), the research effort into understanding expert system usage has been largely theoretical, and little empirical research has yet to emerge (Gregor & Benbasat, 1999; Tan & Hunter, 2002). Moreover, since expert systems introduce a new element by suggesting courses of action, those who do use the technology may choose to ignore or misallocate its recommendations potentially causing the solution to fall short of its promised benefits. For instance, social influences and individual attitudes interact in such a way that when people have poor attitudes or perceptions about a technology and yet social forces strongly encourage its use, people may feign the use of technology but without commitment or without following its prescription (Terry, Hogg, & White, 1999). This aspect has received little if any attention relative to expert systems.

Our empirical study utilized the theory of planned behavior (Ajzen, 1985) to develop hypotheses about the effects of attitudes, perceptions, and social influences on the use and misuse of an expert decision support system technology (EDSS). The theory of planned behavior has been tested in a variety of settings (Sheppard, Hartwick, & Warshaw, 1988; c.f. Hagger, Chatzisarantis, & Biddle, 2002; Klein et al., 2001), and has been the basis for grounding studies in conventional and communications technology adoption (e.g. Morris & Venkatesh, 2000). Because technology effectiveness is essential to perceptions of the technology (Klein et al., 2001), EDSS use and misuse were also treated as independent variables to examine technology effectiveness in terms of the intended goal, which was to reduce human-induced errors.

2. Theory base

Research (e.g. Davis, 1989) has shown that as a technology becomes easier to use, people tend to use the technology more. However, other factors come into play and intervene in the usage behavior, such as whether or not the technology fits the task (Goodhue & Thompson, 1995; Taylor & Todd, 1995), the degree to which people have past experience with the technology (Taylor & Todd, 1995), and whether individual and organizational characteristics are supportive of the technology use (Davis, 1989; Daft & Lengel, 1986; Klobus, 1994; Rogers, 1983; Thatcher & Perrewe, 2002). Hence, people tend to adapt their use of technologies according to the interplay among these myriad of influences (DeSanctis & Poole, 1994; Walsham, 2002). A notable example of this type of adaptation involves social influences (Kraut et al., 1998). The social dimensions in organizations exert strong influence over individual behavior, even to the contrary of personal attitudes about a behavior in some instances (Terry & Hogg, 1996). Regardless of how much an individual may enjoy working with a given technology (Davis et al., 1992), if extreme social norms proscribe such use, he or she may refrain from using it – particularly if cohesion is high and if the organizational unit tends toward collectivism (Tan, Wei, Watson, Clapper, & McLean, 1998; Venkatesh, Morris, & Ackerman, 2000; Walsham, 2002).

Acknowledging the confluences of attitudinal, perceptual, and social forces, the theory of planned behavior (Ajzen, 2001) asserts that three components predict reasoned (as opposed to idiosyncratic) behavior: attitude, subjective norms, and perceived control. Reasoned behaviors are those things people set out to do. The theory of planned behavior framework further asserts that beliefs predicate intentions, which predicate behaviors, and while some attenuation is expected, intentions are immediate precursors of behavior and thus are highly predictive of whether or not people will perform a task (Gagne & Godin, 2000; Hagger et al., 2002).

Attitudes are dispositional factors that comprise positive or negative evaluations of performing a behavior; such as doing "X" is a "good" thing to do. Subjective norms reflect an individual's assessment of social influences from important others, such as managers and coworkers, about performing a behavior. Subjective norms imposed by significant others, such as, "My friends think I should not do X," may discourage performance. Perceived control reflects individual appraisal of successful performance, such as, doing "X" is "easy." Resources, skills, and opportunities must be available for one to have a high degree of perceived control, and it is related to Bandura (1977) concept of self-efficacy in terms of one's cognitive appraisal about one's abilities relative to a behavior (Ajzen, 2001).

3. Expert decision support system usage paradigm

The EDSS usage paradigm consists of following three steps (Taylor & Karlin, 1993). The first step in using an EDSS involves an interactive analytical modeling session to aid in information and context gathering. The EDSS presents a series of displays in response to questions asked by a user who is exploring possible alternatives. Thus with EDSS, users do not have to specify information in advance. Instead, they use the EDSS to find the information needed to generate a solution (Gregor & Benbasat, 1999; O'Brian, 2001).

Characteristic of decision support systems in general, four types of analytical modeling activities are enabled with EDSS: (1) what-if analysis, (2) sensitivity analysis, (3) goal-seeking analysis, and (4) optimization analysis. In what-if analysis, a user makes changes to, or relationships among, variables and then observes the resulting changes in the values. With sensitivity analysis, a value of a single variable is changed repeatedly, and the resulting changes on other variables are observed. Goal seeking analysis reverses the direction of what-if analysis. It sets a target value (a goal) for a variable and then repeatedly changes other variables until the target value is achieved. Finally, optimization analysis is a complex extension of goal-seeking analysis; however, instead of setting a specific target value for a variable, it seeks to find the optimum value for one or more target variables given certain constraints (O'Brian, 2001; Schoemaker, 1993; Resnick, 1992).

Going beyond the modeling capabilities, the second step in EDSS usage involves the execution of case-based and rule-based reasoning for making inferences about alternative decisions. Using case-based reasoning, the EDSS narrows the topics and gathers relevant input from the user and from within its knowledge-bases. The EDSS then interrogates the user about the nature of the problem, searches its knowledge base for facts and rules, and executes its rule-based reasoning processes to govern expert advice given in the explored area (Marquardt, 1993; Taylor & Karlin, 1993). With case-based reasoning, the expert system's knowledge-bases consisting of samples of historical results, occurrences, and experiences, are heuristically searched, exploring for patterns and locating "representative cases" of conditions and events. Rule-based reasoning comprise the rules and statements that govern the actions performed on these representative cases, and take the form of a premise and a conclusion, such as If [condition X] Then [conclusion Y] (Resnick, 1992; Taylor & Karlin, 1993; Zadeh & Kacprzyk, 1992).

Building on its reasoning features, the third and final step in EDSS usage involves the generation of stochastic models (Schoemaker, 1993). The EDSS performs linear and non-linear trending from its case-based and rule-based knowledge to make inferences about the consequences of proposed solutions. Further, because many variables in the problem space may be unknown, it assigns random values (seed values) to factors with unknown states, and subsequently, employs fuzzy logic to generate probabilistic models (Zadeh & Kacprzyk, 1992). These models form the basis for recommendations about courses of action (Resnick, 1992).

Thus, EDSS is designed to simplify complex analysis by automating previously manual functions. Its ability to gather information from disparate sources, apply heuristics, develop semantic models, and generate probabilistic recommendations eases the human burden often encountered in technology-based occupations (Zadeh & Kacprzyk, 1992). Furthermore, these systems have been linked to improvements in technical accuracy of problem identification, improved customer satisfaction, and reduced business expense, making them very effective in their intended goals (Gregor & Benbasat, 1999).

4. EDSS usage and the theory of planned behavior

Ajzen (2001) conception of attitude "refers to the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" (p. 188). While attitudes are linked to both stable and dynamic individual factors (Thatcher & Perrewe, 2002), positive or negative attitudes about technologies are at least partially influenced by how useful a person perceives the technology to be (Gregor & Benbasat, 1999; Taylor & Todd, 1995). To the extent that it facilitates goal-accomplishment, people tend to have higher attitudinal assessment of a technology (Davis, 1989; Klein et al., 2001). Furthermore, perceptions of information and technical quality, including relevance, have had positive implications for attitudinal appraisal (Klobus, 1994), and attitudes improve when there is a "fit" between the task and the technology (Goodhue & Thompson, 1995). Finally, Gregor and Benbasat (1999) found that users are not likely to expend effort to read a system's output unless the material was rendered in a cognitively economical manner. These results suggest that if EDSS is effective in serving in its mission, attitudes are likely to be more positive than if the technology does not produce good results.

Because EDSS provides a structured approach to problem-solving and decision-making within a particular usage paradigm, some users may develop negative attitudes toward the technology (e.g. DeSanctis & Poole, 1994; Klobus, 1994). While users of EDSS may be familiar and experienced with the technology, the technology requires well-defined progressive stages confined to a usage paradigm and this may instill a perception of rigidity and negatively affect one's attitude toward that technology, which in turn, may impinge on the use of the technology (Klobus, 1994; Taylor & Karlin, 1993; Taylor & Todd, 1995). Furthermore, because EDSS is a technology that generates recommendations, there may be latent concerns about trusting what is suggested (Gregor & Benbasat, 1999). Finally, because there an intensified exchange and because the EDSS performs much of the previously manual work using an interrogatory approach, yet the technology is inanimate, the generated recommendations are impersonal, and this may have a negative effect on EDSS usage for some people (Marquardt, 1993).

On the other hand, contemporary application technologies such as EDSS are geared toward solving specific types of problems and generally provide "good-fits" in certain problem domains (DeSanctis & Poole, 1994; O'Brian, 2001). Moreover, EDSS has benefited from years of human factors research and industry standards that have been adopted over the past decade, and these technologies have become commonplace in the field of systems engineering (O'Brian, 2001). A product such as EDSS that reduces human intervention, particularly in mundane tasks such as data gathering, enhances the pleasurably of working with the technology, while simultaneously enriching the problem solution (Davis et al., 1992; Resnick, 1992). When technologies are perceived with favorable attitudes, the likelihood of use increases (Goodhue & Thompson, 1995; Taylor & Todd, 1995); therefore,

H1. Attitude is positively associated with EDSS use.

Subjective norm indicates one's perceptions of significant others' tacit and explicit views about a given behavior (Ajzen, 2001). It reflects a degree of social influence; hence, moderate approval or disapproval a performing an act may be viewed as *encouragement* or *discouragement*; whereas, when social forces reach extremes, the subjective norm becomes perceived as *pressure* to act or refrain from acting (Terry et al., 1999). As social influence increases toward the poles, people strive progressively more to conform to the normative pressure. Thus, subjective norm is surmised to affect technology usage. For example, individuals who observe or hear about important others using a system with positive results, are encouraged to use the system (Kraut et al., 1998). A sample of a persuasive statement provided by a study participant was, "Why do you do it the hard way, just use the tool for that." Conversely, a sample of a dissuasive statement provided by a study participant was, "Can't you figure it out? Why do you have to use the tool for that?" If there is strong sentiment against using a technology among important others, such as peers or supervisors, people are more likely to be dissuaded from using the technology (Terry & Hogg, 1996); thus,

H2. Subjective norm is positively associated with EDSS use.

In addition to attitudes and social forces that may influence whether or not people use a given technology, behavior is influenced by perceptions about how much control one has over an outcome, such as faith in one's ability (Kraut et al., 1998). Hence, perceived control reflects one's perception of ease or difficulty in performing an act (Ajzen, 2001). Perceived control in the use of technologies has been linked with the concept of perceived ease of technology use (Taylor & Todd, 1995). To the extent that using a technology is effortless, people tend to have higher perceived control with the technology (Davis, 1989; Roberts & Henderson, 2000). This aspect is somewhat influenced by training (Bagozzi et al., 1992) and novelty effects (Taylor & Todd, 1995), although as technologies are increasingly infused into American businesses, and as systems become more intuitive, training and novelty effects on technology use are being worn away (Klobus, 1994; Marsh, 1995; O'Brian, 2001).

Nevertheless, the inherent design and usage paradigm of a technology create strong influences in ease-of-use perceptions (DeSanctis & Poole, 1994), as well as whether or not a person believes he or she has the requisite skills and abilities to effectively utilize a given technology (Kraut et al., 1998), and whether there are sufficient resources, organizational support, and ready access to the technology (Klobus, 1994; Thatcher & Perrewe, 2002). As perception of control increases, usage of technology increases concomitantly (Klobus, 1994; Taylor & Todd, 1995). Hence,

H3. Perceived control is positively associated with EDSS use.

The EDSS proposes courses of action for people to take. However, people who use the EDSS may instead choose to rely on their own naïve theories about causes and effects, and prefer their own solutions to those produced by the EDSS. A naïve theory is a well-organized system of explanatory beliefs based on reasoning from everyday experience or commonsense understanding (Wellman & Gelman, 1992).

Nevertheless, because naïve theory is derived from one's belief system, it is subject to biases that may interfere with judgments in planned behavior (Morris & Venkatesh, 2000). Such interference results in biases consistent with beliefs. That is, "Belief-consistent hypotheses are constructed with confirmation rather than falsification as the primary goal. Consequently, belief-relevant evidence is interpreted, dismissed, or reinterpreted as a function of consistency of that evidence with the individual's original theory" (Klaczynski & Narasimham, 1998, p. 175). As an example, studies (Klaczynski & Narasimham, 1998; Stanovich & West, 1999) show that hypothetical arguments are classified as correct or incorrect as a function of the consistency between the arguments' conclusions and the participants' beliefs. Because these biases may create fallibility in judgments, they may be less reliable in terms of the solving complex problems that are targeted by a given technology. Therefore,

H4a. Errors will be negatively associated with EDSS use.

H4b. Errors will be positively associated with EDSS misuse.

While subjective norm, perceived control, and attitude are conceptually different in the theory of planned behavior, the interaction of attitude and perceived control with social influence may exert upward or downward pressure on usage, particularly in cases where there is opposition among these forces (Kraut et al., 1998; Terry et al., 1999). Specifically, people may resort to furtive behavior when they have positive attitudes about performing an act but the subjective norm proscribes the act (Tonglet, 2002). Conversely, when people have negative attitudes or low perceived control toward an act, but the subjective norm encourages participation in an act, people often "go through the motions" but without commitment (Terry et al., 1999).

In terms of technology usage, people may at times resort to subterfuge if they feel compelled to use a technology by their peers or supervisor while holding negative attitudes or low perceived control relative to the technology (Kraut et al., 1998; Terry & Hogg, 1996). Since EDSS goes beyond providing information and gives directions, the effects from attitudes and perceptions of control in relation to social influences may have a bearing on whether or not one follows the recommended directions. Pretending to use the technology while ignoring or disregarding its "output" is a form of subterfuge and constitutes a form of technology misuse. Therefore,

H5. Attitude and subjective norm will be associated in such a way that negative attitudes and positive subjective norms will correspond with greater EDSS misuse.

H6. Perceived control and subjective norm will be associated in such a way that positive perceived control and negative subjective norm will correspond with greater EDSS misuse.

5. Methods

This study took place at a large financial institution, which has one of the world's largest private telecommunications networks that handles both data and voice traffic. Major network hubs reside in Richmond, Charlotte, Atlanta, Jacksonville, Kansas City, Dallas, Chicago, San Francisco, Los Angeles, and Seattle.

Company operations depend on availability and flexibility within its network fabric. To support the core network, it employs over 500 network engineers and administrators. These employees have available an EDSS to analyze network configurations and generate stochastic models of planned network changes, such as adding connections and equipment to the network, or changing software and network parameters.

5.1. Participants

Because attitudes toward technology use may be contaminated by computer anxiety traits (Thatcher & Perrewe, 2002), training (Bagozzi et al., 1992), the degree to which people have past experience with technology (Taylor & Todd, 1995), whether organizational characteristics are supportive of technology use (Davis, 1989; Daft & Lengel, 1986; Klobus, 1994), and personal enjoyment (Davis et al., 1992), a population in which technology is central to their choice of vocation was selected.

Participants were 209 randomly selected network engineers located at the major network hubs residing in Richmond, Charlotte, Atlanta, Jacksonville, Kansas City, Dallas, Chicago, San Francisco, Los Angeles, and Seattle. Questionnaires were distributed to 400 engineers; the response rate was 53%. There were 152 males and 57 females and their ages ranged from 21 to 58 with the average age being 31.75 years (SD = 6.71). All of the engineers were college educated in the fields of computer science, computer information systems, engineering, mathematics, or information technology. Four had associate degrees, 62 had master's degrees, three had doctorates, and the rest held baccalaureates. Years working in the network engineering field ranged from 1 year to 26 years, with the average being 6.8 years (SD = 4.10). Years on the job (tenure) ranged from 1 to 17 years ($\mu = 4.43$, SD = 2.17), and years they had been familiar with the EDSS ranged from 1 year to 4 years ($\mu = 2.79$, SD = 0.93).

5.2. Description of the EDSS

Access to the EDSS was through a desktop workstation to a server. Engineers were presented with a graphical user interface (GUI) that rendered a topographical map of the network core. Using the mouse, engineers could "drill down" into the network topography, gaining finer-grained details about a network region. At the lowest level of the display, near real-time network activity could be visualized for a collection of network segments (parts of the network joined by routers, switches, or other network devices).

A left panel offered modeling options. Models were grouped into three types: analytical modeling options such as "what-if," semantic models, which were concepts and descriptions of services, rules, devices, and other components, and the third group offered stochastic modeling, which were used to generate recommendations. The paradigm was such that a progressive series of steps beginning with analytical modeling were run to develop the requisite context for the stochastic models. During the session, the engineer would ask and respond to questions presented by the EDSS expert system user interface, which would ultimately present the recommendations (See Appendix A for sample stochastic model recommendations). Thus, the EDSS paradigm followed the convention of interactive analytical modeling, execution of reasoning/inference, and the generation of stochastic models.

5.3. Scale development

Since the theory of planned behavior has been tested with good results in a variety of settings, it has been used for the development of hypotheses and items in numerous empirical studies. Hence, the data collection instrument drew upon Ajzen (2001) construction of a standard questionnaire for the theory of planned behavior, and items were bi-polar scaled (−3.00 to +3.00) according to Gagne and Godin (2000) and Ajzen (2001) recommendations (See Appendix C for items). Ten items were presented for each factor (perceived control, subjective norm, and attitude).

A component analysis was run on the data collection instrument, and items were chosen according to Kaiser's rule (Tabachnick & Fidell, 1996) using factor loadings

Table 1
Component analysis, reliabilities, and convergent analysis

	Initial eigenvalues % of variance	Varimax rotation % of variance	Loadings	Scale α reliability	Item wording convergence
PC				0.87	$r = 0.71^{***}$
Item 1	31.26	26.93	0.94		
Item 2	26.73	25.44	0.93		
Item 3	5.32	10.94	0.81		
SN				0.84	$r = 0.58^{***}$
Item 1	27.12	25.42	0.90		
Item 2	25.01	24.97	0.88		
Item 3	12.34	13.79	0.87		
Item 4	5.12	5.44	0.79		
Attitude				0.91	$r = 0.76^{***}$
Item 1	52.51	49.07	0.91		
Item 2	26.72	30.16	0.85		

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

with communalities equal to or greater than 0.7. With eigenvalues set for retention at 1.00, three items for perceived control (accounting for 63.31% of the variance), four items for subjective norm (accounting for 69.59% of the variance), and two items for attitude (accounting for 79.23% of the variance) met Kaiser's criteria. Alpha reliabilities were 0.82 for perceived control, 0.84 for subjective norm, and 0.91 for attitude (See component analysis and alpha reliabilities in Table 1).

A simple test of convergence for item working was performed using two additional items from Warr, Cook, and Wall (1979) attitude scale that were collected and correlated with the attitudinal items. Target wording in the Warr et al. items were changed to tap into attitudes toward the EDSS rather than job attitudes. There was significant correlation between attitudinal components and Warr et al.,'s items ($r = 0.76$, $p < 0.000$). Perceived control was correlated with self-efficacy (Bandura, 1977). Two task-specific self-efficacy items (Locke, Frederick, Lee, & Bobko, 1984) were used, which significantly correlated with perceived control components ($r = 0.71$, $p < 0.000$). Subjective norm was correlated with two items derived from Beersma and De Dreu (2002) group climate items designed to tap into social influence. The correlations were significant ($r = 0.58$, $p < 0.000$), indicating good item working convergence on all three scales.

The dependent variable for "misuse" consisted of three differently worded items on a 7 point Likert scale coded with 1 representing "always ignore the recommendations," and 7 representing "always follow the recommendations." Two control questions for misuse inquired about past behavior. Additional demographic data were collected, consisting of education level achieved, number of years of experience in the field, number of years of experience in the job (job tenure), and number of years the engineer has been familiar with the EDSS application (EDSS familiarity).

5.4. Dependent variables induced errors and usage

Induced errors were those related to an implemented change that was deemed caused by the implementer, such as adding a hardware device, adding a network segment, or changing a software configuration. In other words, the errors were not caused by hardware failure or errors unrelated to a change. The "chain of custody" for tracking both induced errors and usage originated with a counter in the EDSS server. When an engineer accessed the EDSS, he or she supplied a unique login identifier (UID). A counter algorithm logged the usage access and linked the access with the engineer's UID. When the engineer made change in the network, the change description was captured by a software application called a change control system, again using his/her UID. Errors encountered in the network were reported to help desk specialists, who diagnosed the causes of the errors, examined the change control system logs, and identified the engineers who made the changes if the error was human-induced. This process enabled the capture of both EDSS use and changes in which human errors were induced, and tie these to individual engineers.

5.5. Sampling

Midway through the six-month dependent variable data collection, independent variable data was collected about attitudes, perceived control, subjective norm, and behavioral intentions. Participants were also asked to report their intentions to use the EDSS within a week's timeframe, and also inquired about their past week's EDSS usage. However, since objective usage behavior was observable and measurable through the EDSS counter, we elected to omit intention from the reported analysis and concentrate directly on usage behaviors. The availability of objective behavioral measures greatly improves insight into the application of the theory of planned behavior (Morris & Venkatesh, 2000).

6. Results

Table 2 presents the means, standard deviations, and correlations among study variables. There was a slight correlation between attitude and perceived control ($r = 0.20$, $p < 0.05$), which is to be expected (Gagne & Godin, 2000; Hagger et al., 2002), and there was a slight inverse correlation between subjective norm and perceived control (-0.14, $p < 0.05$), both of which are well below the threshold for exclusion recommend by Allison (1999).

Morris and Venkatesh (2000) found a relationship between age and attitude toward conventional technology use. Interestingly, there was no correlation between age and attitude toward EDSS use in this study, likely the result of the technology-oriented vocation of this study's population. There were significant correlations between EDSS familiarity and attitude ($r = 0.13$, $p < 0.05$) and between EDSS familiarity and perceived control ($r = 0.17$, $p < 0.01$).

Table 2
Descriptive statistics and correlations among the study variables

Measure	Mean	SD	1	2	3	4	5	6	7	8
1. Attitude	0.25	1.54	–							
2. Perceived control	0.29	1.32	0.20*	–						
3. Subjective norm	0.15	1.42	0.04	−0.14*	–					
4. Education	4.24	0.65	0.11	0.24**	0.02	–				
5. Age	31	6.71	−0.02	0.06	−0.06	0.19**	–			
6. Field experience	6.80	4.10	0.04	0.04	−0.19**	0.11	0.75**	–		
7. Job tenure	4.43	2.17	0.01	0.13*	−0.05	0.10	0.46**	0.65**	–	
8. EDSS familiarity	2.79	0.93	0.13*	0.17**	0.08	0.14*	0.05	0.04	0.34**	–
9. Use	3.89	1.78	0.57*	0.30**	0.05	0.23**	−0.07	−0.06	−0.01	0.01

Note: Pearson's r. $N = 209$.
* $p < 0.05$.
** $p < 0.01$.

As indicated by the access counter within the EDSS application against self-reported intentions, there was a significant correlation between intention to use and actual use of the EDSS ($r = 0.78$, $p < 0.000$). Of 209 cases, and 33 (16%) did not use the EDSS at all. An exploration of these cases yielded no insight into differences among demographic data for users and non-users.

Using Amos version 4.1 (Arbuckle, 1999), the components were loaded into a structural equation model (SEM) according to the theory (Chin & Todd, 1995). Maximum likelihood estimates (MLE) were used for construct estimation. Although other estimation techniques, such as generalized least squares (GLS) and unweighted least squares (ULS) can be used, MLE is the most common technique (Klein, 1998) and was thus chosen.

The models (technology use and misuse) were run and revised to account for correlated error terms. Four indices were examined for fit (Klein, 1998). The adjusted goodness of fit (AGFI) index measures the amount of variances and covariances jointly accounted for by the model adjusting for the degrees of freedom. The range for AGFI is from 0 (worst fit) to 1 (best fit); an AGFI >0.8 is desirable. The likelihood ratio is the value of chi-square divided by the degrees of freedom, and smaller than three is desired. The root mean square error of approximation

Table 3
Model fit

Indices	Use	Misuse
Df	191	190
χ^2	274.53	227.11
Probability	0.000	0.34
AGFI	0.85	0.87
Likelihood Ratio (χ^2/df)	1.44	1.20
RMSEA	0.06	0.03
R^2	0.45	0.77
R^2 Errors	0.68	0.44

(RMSEA) measures model accuracy according to population discrepancy in relation to degrees of freedom; an RMSEA <0.05 is desired, and a chi-square probability score >0.05 is desired (Nunnally & Bernstein, 1994).

As seen in Table 3, although the technology use model showed a significant chi-square value, the other three indices showed reasonable fit (Nunnally & Bernstein, 1994), χ^2 (191, 209) = 274.53, $p = 0.000$, adjusted goodness of fit (AGFI) = 0.85, likelihood ratio 1.44, and root mean square error of approximation (RMSEA) = 0.06. The misuse model showed good fit according to the four indicators (Nunnally & Bernstein, 1994), χ^2(190, 176) = 227.11, $p = 0.34$, adjusted goodness of fit (AGFI) = 0.87, likelihood ratio 1.20, and root mean square error of approximation (RMSEA) = 0.03. However, there was violation of the assumption of linearity for misuse (discussed below) and analyzed using hierarchical regression with quadratic terms.

The SEM for technology use is shown in Fig. 1. The first hypothesis (H1) stated that employees with more positive attitudes would use the EDSS in greater proportion than those who held negative attitudes. This was supported ($\beta = 108.94$, $p < 0.05$).

The second hypothesis (H2) predicted that employees with more positive subjective norms would use the EDSS in greater proportion than those who held

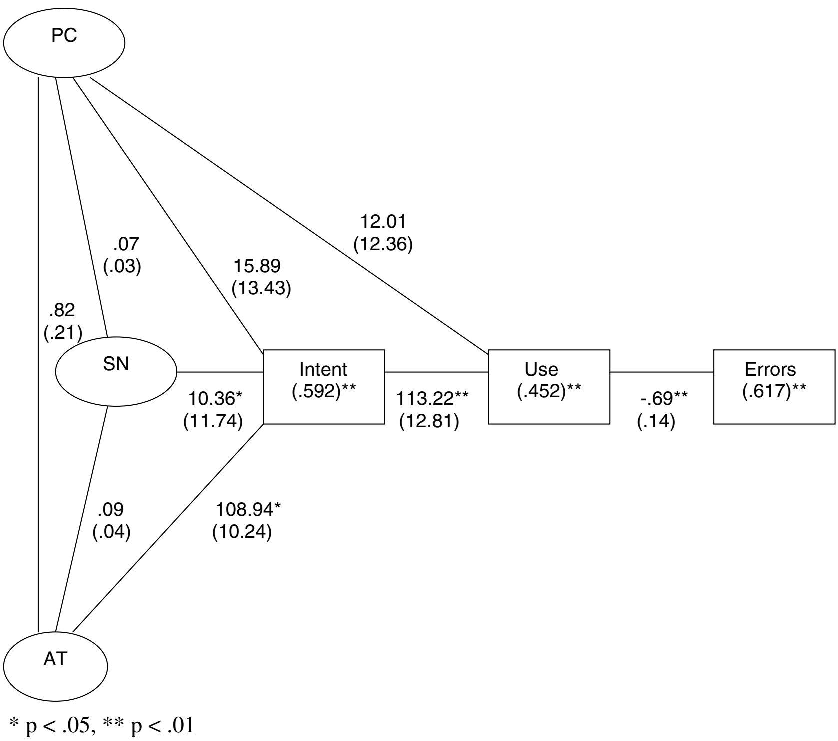

Fig. 1. Technology Use Model.

Table 4
Hierarchical regression results for misuse

Degree of misuse $N = 176$	R^2	Adjusted R^2	ΔR^2
Step 1 Attitude	0.425	0.421	0.425***
Step 2 AT^2	0.510	0.502	0.031**
Step 3 Subjective Norm (SN)	0.479	0.473	0.055**
Step 4 Attitude × SN	0.531	0.520	0.020***
Step 5 Attitude^2 × SN	0.556	0.543	0.026**

** $p < 0.01$.
*** $p < 0.001$.

negative subjective norms; this was supported ($\beta = 10.36$, $p < 0.05$). The third hypothesis stated that employees with greater perceived control would use the EDSS in greater proportion than those who have lower perceived control. However, this was not supported ($\beta = 15.89$, n.s.).

People may rely in their naïve theories rather than follow the recommendations of the EDSS. Since the EDSS is designed to work forward from a logical progression of steps through to the generation of stochastic models, ignoring the recommendations constitutes a misuse of the technology. Consequently, the full benefits of the technology may not be realized in these cases. Hypothesis H4a suggested that employees who more frequently used the EDSS would have fewer induced errors than employees who used EDSS with less frequency. As seen in Fig. 1, intention significantly predicted technology use ($\beta = 113.22$, $p < 0.01$), and technology use led to fewer induced errors ($\beta = -0.69$, $p < 0.01$). Hence, hypothesis H4a was supported. Similarly, hypothesis H4b stated that employees who adhered to the EDSS recommendations with more frequency would have fewer induced errors than employees who more frequently disregarded the recommendations. Again, this hypothesis was supported ($\beta = -0.18$, $p < 0.05$).

Because social influence may elevate furtive behavior (Terry & Hogg, 1996), for hypotheses H5 and H6, interactions were proposed. Hypothesis 5 (H5) suggested that attitude and subjective norms would be associated in such a way that more negative attitudes and greater subjective norms would correspond with greater incidence of EDSS misuse. The interaction was significant ($\beta = 0.329$, $p < 0.000$), and a plot of the relationship (Cohen & Cohen, 1983) revealed a non-linear $\cap$ shape. Therefore, to test this relationship, a hierarchical regression using quadratic terms was conducted according to Aiken and West (1991) recommendations. Attitude was entered in step 1, followed by the quadratic (X^2) terms in step 2, subjective norm in step 3, and followed by the linear moderator and quadratic-by-linear term in steps 4 and 5. As seen in Table 4, there was a significant curvilinear relationship ($\Delta R^2 = 0.026$, $p < 0.01$). Hence, when attitudes are poor, and subjective norms are high, there is a non-linear increased tendency to misuse the technology.

Hypothesis 6 (H6) made a similar assertion as H5 only with regard to perceived control. It suggested that perceived control and subjective norms would be associated in such a way that more perceived control and greater subjective norms would correspond with EDSS misuse. The interaction term was not significant ($\Delta R^2 = 0.007$, $p = 0.356$, n.s.); hence, this hypothesis was not supported.

7. Discussion

The theory of planned behavior (Ajzen, 1985) has been widely tested, and studies have employed the theory in the development of empirical studies of communications or conventional information technology use (e.g. Klein et al., 2001; Taylor & Todd, 1995). Where communications technologies facilitate co-evolution of problem solving and decision making among people, EDSS and other expert systems create a transaction between user and computer where ultimately, the computer generates the recommended course of action. This also differs from decision support tools that merely gather information to inform a human decision maker. Consequently, new questions are raised about the use of the expert system technology, and additionally, about the effects if the technology is misused.

7.1. Implications for research

Using the theory of planned behavior, we inquired into whether or not the EDSS was effective in terms of its mission, which would have a bearing on the perceived usefulness of the technology and hence on attitudes. We found that as the use of EDSS increased, the number of human-induced errors decreased. We also found that using the EDSS paradigm and following the recommended courses of action resulted in fewer human-induced errors than did misusing the EDSS technology.

We also found that positive attitudes and greater perceived control led to increased EDSS use. We also found differences among those who felt encouraging versus discouraging subjective norms. However, other research (Hagger et al., 2002; Terry & Hogg, 1996) has failed to confirm subjective norm influences on technology use. In particular, Morris and Venkatesh (2000) found that the subjective norm influences attenuated over time. As with the aforementioned study, our study involved an American company. This finding may not be the case in cultures that are more collectivistic (Walsham, 2002).

As with expert systems in general, because EDSS introduces the prospect of furtive behavior, that is, engineers may pretend to use the technology but ignore or misuse its "output," social influences were surmised. For instance, Terry et al. (1999) found that people strive to behave consistent with their attitudes only when there is a supportive normative climate. Conversely, Tonglet (2002) found that even in the face of strongly opposing subjective norms, people engage in furtive behavior if their attitudes are positive about performing an act. It has also been found that while attitudes and subjective norms are intertwined, that is, persuasion by important others may influence attitude, strong subjective norms are more likely to affect *how* people use a technology, not *whether* they use a technology (Kraut et al., 1998).

Our investigation found a non-linear relationship between attitude toward the EDSS and subjective norm. As subjective norm increases toward support for EDSS use, in conjunction with positive attitudes, usage of the EDSS increased. However, as attitudes became more negative, and subjective norm increased toward the polar extreme, engineers increased their furtive behavior by misusing (ignoring) the EDSS recommendations. These findings suggest that people attend first to personal attitudes, which is consistent with an individualistic culture. An interesting question then emerges, would this condition be found in a collectivistic culture?

Another question that emerges about subjective norm involves gender. Venkatesh et al. (2000) found differences in the susceptibility of subjective norm influences between male and female gender. However, we found no such relationship. This may be partly explained by an important limitation of our study: our sample was predominately male by more than a 3 to 1 margin. A more balanced study population may yield different results.

Unlike the relationship between attitude and subjective norm, our study also found no interaction between perceived control and subjective norm on whether or not engineers misused the EDSS. Our conjecture is that because the study's organizational structure, through policy, was supportive of EDSS use, which is important to perceived control (Klein et al., 2001), and because the study population was skilled in the technology (an essential component of perceived control), conditions may not have been set opposition sufficient for a finding. However, our finding may also be subject to an important limitation. Following the recommended item wording from Ajzen (2001) construction of a standard questionnaire did not elucidate reasons for perceived control, and our study did not sufficiently explore the rationale behind perceived control. During data collection, some of the participants informally suggested that they felt using the EDSS gave up control to the technology, where others informally stated that they perceived greater control with the technology. While adjusted items significantly loaded on the construct, there may still be ambiguity about the notion of "control" in the context of technology use.

7.2. Implications for practice

The impact of information systems technology use is significant. Spending estimates for information systems technologies are \$1.26 trillion per year worldwide (Morris, 2002). Among the fastest growing information technologies are decision support systems applications, which comprise a \$1.3 billion per year industry in the United States (Aberdeen Group, 2002; Morris, 2002; Venkatesh et al., 2000). Yet as much as 25–30% of information technology goes unused after purchase (Aberdeen Group, 2002; Bagozzi et al., 1992), representing nearly \$400 million annually in the United States decision support systems market alone (Morris, 2002).

Practitioners are interested in technology use in part to improve the effectiveness of their organizational capabilities. This study found that EDSS use was related to fewer induced errors. Disuse and misuse create at least two problems: companies may be investing heavily in technology that goes to waste, and in such instances, they are unable to leverage the returns on the promised benefits that the technology has to offer. An examination of the responses indicated that when people have a high degree of trust, they tend to follow the recommendations made by the technology, and when they have a low degree of trust they may or may not to follow the directions. Respondents indicated at least a moderate or greater level of intention to use the EDSS, however, the difference between those with low trust and their higher level of intention to use EDSS may be accounted for by a feeling of guilt for not using it. In other words, those who had low trust but expressed higher intentions to use EDSS also indicated higher degrees of guilt feelings for misusing EDSS.

Our findings suggest at least three strategies to mitigate the problems of non-use and misuse in the field. Since our study population involved people who by definition work with technology, one explanation for misuse is related to attitudes about the nature of the computer-generated recommendations, which may cause users to have reservations about trusting what is suggested (Gregor & Benbasat, 1999). To the extent that managers can quantify and educate personnel about the results of using the technology, this should lead to increased confidence in the technology. Next, just as training has been linked with increased technology use (Bagozzi et al., 1992), this study found a correlation between the lengths of time engineers used the EDSS and positive attitudes as well as increased perceived control. Hence, managers may want to focus on techniques beyond training that encourage consistent and continued use. Some companies have offered monitory rewards such as bonuses for such practices. Finally, since negative attitudes and strong subjective norms were found in this study to lead to increased furtive behavior, building an accepting, supportive (rather than coercive) environment would likely expose use from non-use and reduce pretense. In such an environment, managers would be in a better position to diagnose the root causes and address the issues of non-use.

Appendix A. Sample stochastic model recommendations

Probability 99.8%: access list set to filter:: = Ethernet 0:: = upon exit. *Recommend*: filter departure packets:: = from the interface to internet:: = 112.055.113.000:: = to preclude unfiltered access to:: = 100.051.020.00.

Probability 67.2%: planned change:: = upgrade:: = 134.022.333.023:: = will cause:: = 121.433.433.000:: = become saturated from:: = between:: = 10.52. EST:: = and:: = 13.31. EST:: = causing latency of:: = 31ms:: = for the following services:: = TCP/IP, FTP,:: = affecting the following applications/transactions:: = BankAppxfer, BranchUpdate, BranchUpdate,:: = cost metrics:: = $2100:: = per ms, *Recommend*: concurrent upgrade:: = 10–100 ms Ethernet of:: = 126.014.023.000:: = estimated cost:: = $14,540:: = estimated savings:: = $1850 ms.

Probability 58.3%: planned change:: = upgrade:: = 130.022.033.023:: = will cause:: = 125.033.015.000:: = become saturated from:: = between:: = 11.12. EST:: = and:: = 12.15. EST:: = from:: = 13:00. EST:: = and:: = 15:12. EST:: = causing latency of:: = 60 ms:: = for the following services:: = SMTP, HTTP, X.500/LDAP,:: = affecting the following applications/transactions:: = Lotus Notes, BankApp, authentication, *Recommend*: add route:: = 130.022.033.000:: = interface 1, Cisco 1750 Router, Ethernet 10/100BaseTX, 32Kbs non-volatile, 8192Kbs, ISDN BRI (64Kbs), IOS C1700-SV3Y-M, 12.0(19980308:184442).

Appendix B. Technical note

There were rules in the EDSS geared around "constraint categories" to resolve recommendation conflicts. Constraint categories for an explored area included: maintainability, reliability, cost, schedule, security, configuration, performance, interoperability, compatibility, availability, recovery, and so forth. If, for instance, a proposed network change might result in a network outage, the result would fall under the availability category. If on the other hand, the change would slow the traffic (increase latency), this would fall under performance. These categories (and problems within categories) were weighted to resolve conflicts or paradoxes among decision alternatives. For instance, because outages were weighted more heavily than performance, if a proposed change had a high probability that it would result in performance degradation, and forgoing the change had a high probability that it might result in an outage, the EDSS would recommend making the change.

Appendix C. Items

Perceived Control (PC)

	For me, using [EDSS] for network modeling	
Is difficult	:____:____:____:____:____:____:____:	Is easy
Impedes my decision making	:____:____:____:____:____:____:____:	Assists my decision making
Precludes my skills	:____:____:____:____:____:____:____:	Facilitates my skills

Subjective Norm (SN)

	Regarding [EDSS], most people who are important to me	
Think I should not use it	:____:____:____:____:____:____:____:	Think I should use it
Do not support using it	:____:____:____:____:____:____:____:	Support using it
Discourage me from using it	:____:____:____:____:____:____:____:	Encourage me to use it
Do not use [EDSS]	:____:____:____:____:____:____:____:	Use [EDSS]

Attitude

	For me, using [EDSS]for network modeling is	
Bad	:____:____:____:____:____:____:____:	Good
Unpleasant	:____:____:____:____:____:____:____:	Pleasant

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