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International Conference on Information Systems (ICIS)

December 1996

Explaining the Effect of Incentives and Control Mechanisms on Information Technology Usage: A Theoretical Model and an Empirical Test

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EXPLAINING THE EFFECT OF INCENTIVES AND CONTROL MECHANISMS ON INFORMATION TECHNOLOGY USAGE: A THEORETICAL MODEL AND AN EMPIRICAL TEST

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Abstract

Current theories of information technology (IT) usage do not include the role of managerial incentives and control mechanisms in motivating individual IT usage behavior. Drawing on agency theory in the microeconomics literature, this paper develops a principal-agent model (PAM) of intraorganizational IT usage which addresses this issue. This model is empirically validated using data collected from a laboratory experiment. PAM and TAM (technology acceptance model) variables are then combined within a TPB (theory of planned behavior) framework to propose an integrated model of IT usage. A comparison of the explanatory power of PAM, TAM, and the integrated model indicates that explanation of IT usage can be increased by adding incentives and control as additional determinants of behavioral intention, over and above the attitudinal variables in TAM.

1. INTRODUCTION

Incentives and control mechanisms are often considered powerful motivators of human behavior (Eisenhardt 1989; Nilakant and Rao 1994). However, much of the research to date have overlooked the role played by these variables in influencing individual behavior related to IT usage. The current study examines the effect of incentives and control on intraorganizational information technology (IT) usage by developing a theory-based model of IT usage and then testing the model using data collected from a laboratory experiment. The research questions addressed are why and how do incentives and control affect intraorganizational IT usage, and what is the relative contribution of these variables to usage compared to attitudinal variables suggested by prior usage models.

Current models of IT usage, such as technology acceptance model (TAM) (Davis, Bagozzi and Warshaw 1989), attempt to explain usage in terms of individual variables such as beliefs, attitudes, and intentions related to IT usage. However, subsequent empirical research has revealed two shortcomings of these models. First, these models explain only about 35 percent of the variance in IT usage, suggesting the need to look beyond the traditional intention-based models of cognitive psychology in seeking additional determinants of usage (Taylor and Todd 1995). Second and more importantly, though these models explain IT usage reasonably well in personal-use contexts (e.g., computer use at home), their usefulness may be limited in organizational contexts where users' behavior is not within their complete volition but is rather influenced by managerial actions (Fichman 1992).[2] Research indicates that managers can encourage or discourage intraorganizational IT usage explicitly via managerial mandates or control over infrastructure supporting usage (e.g., training, physical access to hardware/software, etc.) and/or implicitly via usage incentives and organizational reward systems (Leonard-Barton and Deschamps 1988). Hence, managerial influences must be included in any intraorganizational IT usage model.

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[1]The author is grateful to Randy Cooper and Richard Scamell for their help at various stages during this research project and Wynne Chin for providing a beta version of his PLS-Graph software for data analysis. The author also thanks the Associate Editor and three anonymous reviewers for their valuable comments on an earlier version of this paper.

[2]Though few prior TAM-based studies (e.g., Davis, Bargozzi and Warshaw 1989) were conducted using organizational users, the managers in these settings were either not in a position or did not want to influence usage.

The current study addresses these limitations by specifically looking at two aspects of managerial influence: incentives and control. A principal-agent model (PAM) of IT usage is developed based on agency theory in the microeconomics literature, which is then integrated with TAM within a theory of planned behavior (TPB) framework (Ajzen 1991). Empirical analysis indicates that (1) PAM variables do have significant effects of intraorganizational IT usage and (2) addition of PAM can explain about 9 percent of user's behavioral intention to utilize IT, over and above TAM's attitudinal variables. It is suggested that PAM complements TAM while extending usage models from personal-use to organizational-use contexts.

This paper proceeds as follows. The second section describes the theoretical underpinnings of the proposed model of IT usage. Section three discusses methodological issues related to empirical testing of this model. Section four describes the data analysis procedures employed and analyzes the findings. Section five highlights potential contributions of the findings to MIS research. The final section discusses limitations of the study and suggests avenues for further research.

2. A THEORETICAL MODEL OF IT USAGE

A principal-agent relationship is said to exist whenever two parties are involved in a business relationship such that the payoffs of one party (principal) depend on the actions of the other (agent) (Arrow 1985; Sappington 1991). The principal owns the means of production but does not possess the time or ability to produce the desired output, and therefore hires an external agent to perform the task on his/her behalf. However, the agent may not share the same goals as the principal, and thus the agent's rational choice of behavior may be inconsistent with the principal's interests. The principal-agent model (PAM) attempts to resolve this agency problem by suggesting incentive schemes ("contracts") and/or control mechanisms (e.g., monitoring) that can coalign the agent's goals with that of the principal, and thereby motivate the agent to behave in the principal's best interests (Sappington 1991).

The typical sequence of events in PAM is as follows (Sappington 1991). The principal designs a contract, specifying incentives to be awarded to the agent for different possible outcomes. The agent decides whether to accept or reject this contract. In case the contract is rejected, the relationship is terminated. If the agent accepts the contract, he/she observes a "state of nature" (exogenous variables that are unpredictable and outside the control of either party) and decides how much effort to put forth. The agent's decision is influenced by three factors: (1) amount and type of incentives available, which provide utility to the agent, (2) effort required to perform the task, which provides disutility, and (3) the agent's observation of the state of nature, which mediates the effect of expended effort on the realized outcomes. Taking these factors into consideration, the rational agent selects an effort level that maximizes his/her payoffs. The principal cannot see the actual effort expended by the agent but observes the realized outcomes, based on which the agent is rewarded as promised in the contract.

In PAM, the principal's problem is designing ex ante incentive schemes that can minimize agency costs (costs incurred by the principal in motivating, monitoring, and ensuring the commitment of the agent), while the agent is concerned with selecting an effort level that maximizes his/her utility for a given incentive scheme. As such, PAM equates the design of contracts to reconciling the agent's utility maximization problem and the principal's cost minimization problem (Nilakant and Rao 1994). In doing so, PAM makes some assumptions: that human beings (both principals and agents) are rational, risk-averse, and may indulge in opportunistic behavior to further their own goals (Eisenhardt 1989), and that organizations are characterized by partial goal incongruence, costly and imperfect information, and production efficiency (i.e., outcomes vary directly with the quantity of effort expended) (Eisenhardt 1989).

IT usage within organizations can be modeled in the form of a principal-agent relationship, by viewing IT management as the principal and individual users as agents. From a rational perspective, managers acquire IT to achieve organizational benefits, such as increased productivity of their knowledge workers (Curley and Pyburn 1982), improved decision making (Keen and Scott-Morton 1978), or enhanced competitiveness in the business environment (Ives and Learmonth 1984), and want organizational members to appropriately utilize the IT so that the intended benefits are realized.[3] However, individual users typically value personal goals over management objectives (Francik et al. 1991), hence the conflict of interests. IT usage often requires users to expend effort in overcoming usage barriers such as learning curves (Attewell 1992) and social inertia (Keen 1981), and may be therefore resisted by users (Markus and Robey 1988). PAM holds that managers can induce potential users to utilize the IT by providing them with incentives (e.g., commissions, promotions, praise) for IT use and/or penalties (e.g., threats, dismissals) for non-use. Users' behavior is therefore affected by availability and type of incentives, effort required to utilize the IT, and "state of nature" or environmental variables affecting IT usage (e.g., IT accessibility). The mapping between PAM and intraorganizational IT usage is depicted in Table 1, while the conceptual research model employed to model users' decision regarding IT usage is presented in Figure 1.

Table 1. Structural Similarities between the Principal-Agent Model and Intraorganizational IT Usage

Principal-agent model	*Intraorganizational IT usage*
Principal	Management
Agents	Organizational users
Contract	Usage incentives offered by management
State of nature	Environmental variables that affect IT usage
Behavior	IT usage by individual users
Outcome	Organizational effectiveness of using IT

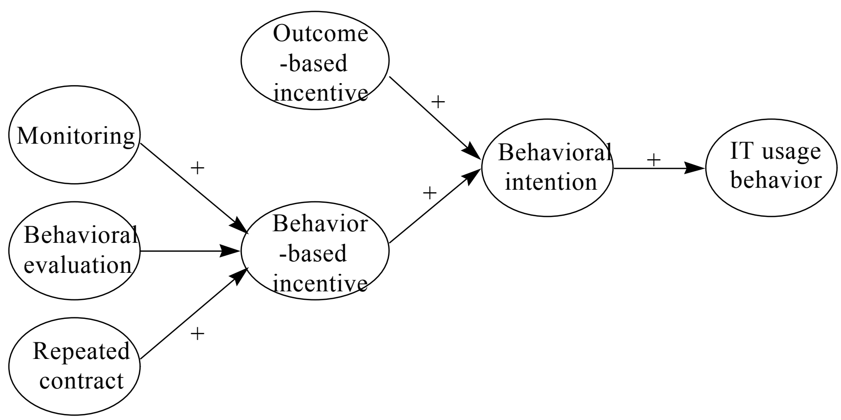

Figure 1. The Principal-Agent Model of Intraorganizational IT Usage

Note: Due to the nominal nature of behavioral evaluation, no directionality can be associated to the behavioral evaluation–repeated contract relationship. Behavioral intention is the inverse of goal incongruence.

[3]IT usage beyond a certain point may yield diminishing marginal returns, which may not be favored by managers. Either under-use or over-use can be construed as "inappropriate," which is accounted for in PAM by focusing on appropriate use rather than usage in general.

At the heart of the proposed model is the notion of *goal incongruence* between management and users, which may cause rational users to behave against the management's interests. Goal incongruence can be defined as the difference in intention between managers and users regarding IT usage. Since the management's goal is to have all users appropriately utilize IT provided to them (because such utilization is expected to eventually lead to organizational benefits), goal incongruence in this study refers to users' behavioral intention to *not* utilize IT. Prior implementation research (e.g., Davis, Bargozzi and Warshaw 1989) demonstrates that behavioral intention is positively related to IT usage, thereby supporting the hypothesized negative association between goal incongruence and usage. As indicated in Figure 1, goal incongruence is henceforth defined in terms of behavioral intention.

PAM posits that incentives provided by managers may motivate user behavior by coaligning the goals of users with those of managers. Such incentives may be categorized along two dimensions: (1) *incentive level:* low versus high, and (2) *incentive type:* behavior-based (e.g., monthly pay) versus outcome-based (e.g., commissions based on sales) (Ouchi 1979; Nilakant and Rao 1994). The higher the incentive level, the greater the coalignment of goals between management and users, and the greater the users' motivation to utilize the IT. Likewise, outcome-based incentives are more effective in ensuring the commitment of users than behavior-based incentives, because they transfer the risks of IT utilization to the users, making users accountable for the realized outcomes. In contrast, behavior-based contracts insure users from potential unfavorable outcomes due to non-use of IT, and thereby may induce them to shirk from the intended behavior. In Figure 1, in order to indicate directionality in PAM associations, the incentive type construct is separated into its polar types and weighted with incentive level, to yield outcome-based and behavior-based incentives (each ranging from low to high).

Though outcome-based incentives are generally more effective in motivating user behavior, such incentives are often resisted by risk averse users, because of the additional risks they impose on potential users. Under such circumstances, managers may be forced to offer behavior-based incentives (Eisenhardt 1989). The design of behavior-based incentives is, however, complicated by the managers' inability to observe or infer users' actual behavior and/or perceived state of nature, potentially leading to information asymmetry problems such as "moral hazard" and "adverse selection" (Sappington 1991). In a moral hazard problem, opportunistic users take advantage of the manager's ignorance of their behavior to put in less effort than expected. In adverse selection, the manager's unawareness of the state of nature (as perceived by users) may lead to the design of ineffective incentives, since the state of nature is reflected in users' choice of effort level but not factored into the managers' design of incentives.

PAM recommends three approaches, directed at controlling user behavior, to overcome information asymmetry problems (Nilakant and Rao 1994). *Monitoring* mechanisms (e.g., computer logs, time sheets, spot checks by supervisors) may help reduce user opportunism in moral hazard settings by informing the management of user behavior (Sappington 1991). Although monitors do not provide accurate information about user behavior (e.g., a console log may indicate how much time a user is logged on to a computer system, but will not indicate whether the system was appropriately utilized), they are perceived by users as revealing their behavior to the management, which induces them not to "cheat" the management with the promised effort level.

The adverse selection problem can be partially mitigated, in multiple-agent or multiple-period settings, by employing incentive schemes based on *relative evaluation of behavior* or *repeated contracts*. In a multiple-agent setting, since the same state of nature is observed by all users, evaluation of user behavior relative to his/her peers (e.g., promotion of one user from within a group of users based on IT utilization) may help control for the state of nature common to all users, albeit unknown to management. Under such circumstances, users may be motivated to outperform their peers in order to obtain the highest reward (Sappington 1991). Likewise, if users' incentives in future periods are tied to their behavior in the current period (e.g., short-term contracts renewable at the end of the period), they may be motivated to utilize the IT appropriately in the current period in order to secure favorable incentives in subsequent periods (Eisenhardt 1989).

Note that control mechanisms, such as monitoring, behavioral evaluation, and repeated contracts, are only relevant to behavior-based incentives, since outcome-based incentives, by their very nature, ensure users' commitment by making them accountable for the realized outcomes. In other words, although information asymmetries may exist for both incentive types, opportunistic behavior is realized only with behavior-based incentives. Hence, as shown in Figure 1, these control variables do not directly affect IT usage or goal incongruence, but rather have a indirect effect via incentive type.

The positive effects of incentives (both monetary and non-monetary) on usage are empirically supported by Howard and Mendelow (1991) and Currid (1995). The effects of monitoring were examined by Irving, Higgins and Safayeni (1986) and Aiello (1993) in field and laboratory settings respectively, and the results indicate that perceptions of monitoring improve quantity and quality of IT usage, though unfavorable side-effects such as increased stress, decreased satisfaction, and decline in peer relationships were also observed. However, little empirical research has been directed at investigating the effects of incentive types, behavioral evaluation, or repeated contracts on IT usage. The next section represents such an effort.

3. RESEARCH METHODOLOGY

This section describes methodological issues concerning the empirical testing of the principal-agent model, and is organized into three parts. The first part describes the research setting, subjects, and tasks employed in this study. Operationalization and measurement of research variables are addressed next. The final part describes psychometric validation of the research instrument used to measure these variables.

3.1 Research Strategy

A laboratory experiment was used to empirically test the proposed model of IT usage. Selection of this approach was motivated by two reasons. First, given that research related to incentives and control is in its formative stages, internal validity (causality among variables) is considered more crucial compared to external validity (generalizability to other contexts). Laboratory experiment can provide high levels of internal validity by employing rigorous controls on the variables of interest. Second, inadequate treatment manipulation has been cited as one of the reasons behind the lack of significant results in research on incentives (Eisenhardt 1989). Difficulty in manipulating treatment variables related to incentives and control in field settings limits the utility of field-based approaches for the current problem.

Students from a sophomore-level business applications class at a large southwestern university served as subjects for this laboratory study. Subjects received bonus points toward their class grade for participating in an optional, extra-credit assignment (a managerial budget allocation problem) that involved the potential use of a new software tool (Microsoft Excel's SOLVER). Prior to the experimental treatment, an in-class demonstration was conducted to show how to perform such tasks using various IT and non-IT means. Subjects were also provided with a written tutorial so that they could practice using the IT prior to the treatment.

On the scheduled date, subjects were randomly allocated among six treatment groups (described in the next section) and asked to complete a pre-treatment questionnaire intended to elicit their perceptions of model variables. They were then given the experimental task and asked to complete it using any IT or non-IT of their choice. On task completion, subjects were asked to save their work on diskettes, which could be evaluated at a later time, and were administered a post-treatment questionnaire intended to assess their perceptions of IT usage.

The task selected for this study was a managerial budget allocation problem that could be facilitated by the use of IT. In this task, subjects assumed the role of a marketing manager of an appliance store and were asked to determine the exact number of refrigerators, stoves, and microwave ovens to purchase, subject to budgetary, warehouse, and back order constraints, in order to take advantage of a promotional dealer pricing for selected models of these products. Such a task is fairly typical of problems faced by marketing managers (IT users) in organizational settings (McIntyre 1982), and has been employed in slightly different forms in prior MIS research (e.g., Benbasat, Dexter and Todd 1986; Szajna and Scamell 1993). The reasonableness of this task for the subject sample was verified from an initial pilot study.

Microsoft Excel's SOLVER (a tool for solving linear and integer programming problems) was the IT recommended for performing the assigned task. Subjects were told that SOLVER was particularly suited for complex tasks of this type and that it enhanced user productivity by decreasing the time expended and reducing potential errors in performing such tasks. However, subjects were free to use any other IT or non-IT of their choice (e.g., by using a hand calculator or trial-and-error techniques in Excel). This degree of freedom was necessary to ensure that subjects' use of IT was voluntary. Note that although Excel was taught as part of this class, the SOLVER tool was not part of the curriculum and was not covered in class.

A pilot study revealed that over 98 percent of the students in this class did not have any prior exposure to this tool, and, therefore, it was considered acceptable for examining subjects' IT usage behavior.

3.2 Operationalization of Variables

Nine research variables, in addition to IT usage, were examined in this study. Five of these variables (i.e., incentive level, incentive type, monitoring, behavioral evaluation, repeated contracts) were indigenous to PAM, while the remaining four (i.e., ease of use, usefulness, attitude, and behavioral intention) were adapted from TAM (Davis, Bargozzi and Warshaw 1989).[4] In addition to PAM, TAM was also tested as a benchmark for comparing the explanatory power of the proposed model (PAM) and that of an integration of TAM and PAM variables within a common TPB framework.

The experimental design employed was a randomized blocks design (see Table 2) with five treatment variables (i.e., incentive level, incentive type, monitoring, behavioral evaluation, and repeated contracts). Each of these variables were manipulated dichotomously (i.e., low versus high, present versus absent), by randomly assigning subjects into six treatment groups. The purpose of this manipulation was to induce variance in these variables so that their effects on the dependent variables could be easily detected.

Table 2. Experimental Design

Low incentives		High incentives			
No repeated contract	Repeated contract	Outcome-based incentives	Behavior-based incentives		
			Relative behavior	Absolute behavior	
				No monitoring	Monitoring
Treatment group 1	Treatment group 2	Treatment group 3	Treatment group 4	Treatment group 5	Treatment group 6

Incentive level was manipulated as low versus high depending on whether subjects received two or seven points toward their grade for their use of SOLVER.[5] Incentive type was manipulated by dividing the high incentive group into two parts; the first group (behavior-based incentives) was rewarded based on their extent of SOLVER usage, whether or not they could solve the problem, while reward for the second group (outcome-based incentives) was linked to their solving the problem irrespective of SOLVER use/non-use. To manipulate behavioral evaluation, a portion of the behavior-based incentive group (relative behavioral evaluation) was informed that their SOLVER utilization would be evaluated relative to that of other subjects in the same group, while the remaining subjects (absolute behavioral evaluation) were evaluated on an absolute scale. Monitoring was manipulated by informing a section of the absolute-behavioral evaluation group that their use/non-use of SOLVER was being monitored continuously by a network monitoring software, while the other section was told that they were not being

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[4]TAM holds that two sets of perceptual beliefs – usefulness and ease of use – predict individual attitude toward IT, which, in turn, influences their behavioral intention and IT usage.

[5] The specific number of points was determined from a pilot study, where subjects were asked what they would consider to be a reasonable incentive for this task. Of the subjects, 90 percent agreed that four to five points would be adequate. Therefore, a mean incentive level of 4.5 with a spread of five points was utilized.

monitored. Repeated contract was manipulated by informing some subjects in the low incentive (behavior-based) group that they could get an additional five points on a similar task if they utilized SOLVER appropriately in the current task, while others (no repeated contract) did not have any such opportunity. The low incentive group was used for this purpose (rather than high incentive group) in order to provide more students with the opportunity to obtain seven points from this task.

Subjects' perceptions of these treatments were measured using multiple-item, 7-point Likert scales and used for data analysis, since individual behavior depends not on actual treatments but rather on users' perceptions of such treatments (Moore and Benbasat 1991). The unmanipulated variables (i.e., goal incongruence, attitude, usefulness, and ease of use) were also measured perceptually using prevalidated scales from the IT implementation literature (e.g., Davis, Bargozzi and Warshaw 1989; Moore and Benbasat 1991; Taylor and Todd 1995). Operationalization of these variables is presented in Table 3, and the actual questionnaire is provided in the appendix.

Table 3. Operationalization of Variables

Variable	*Operational measure*	*Mode of measurement*	*Scale*	*Source*
Incentive level*	Degree to which incentive provided is perceived as being high or low	Three-item perceptual measure	Interval	None
Incentive type*	Degree to which incentive provided is perceived as behavior- or outcome-based	Three-item perceptual measure	Interval	None
Monitoring*	Degree to which subjects believe that their SOLVER usage was being monitored	Three-item perceptual measure	Interval	None
Behavioral evaluation*	Degree to which subjects believe that their incentive was based on absolute or relative behavior	Three-item perceptual measure	Interval	None
Repeated contract*	Degree to which subjects believe that they can receive more incentives if current task is performed well	Three-item perceptual measure	Interval	None
Behavioral intention	Degree to which subject intends utilizing SOLVER during the task (behavioral intention)	Three-item perceptual measure	Interval	Mathieson (1991)
Usefulness	Degree to which SOLVER use is perceived as enhancing task performance	Three-item perceptual measure	Interval	Davis, Bargozzi and Warshaw (1989)
Ease of use	Degree to which SOLVER use is perceived as being free of physical/mental effort	Three-item perceptual measure	Interval	Moore and Benbasat (1991)
Attitude	Overall positive or negative predisposition toward SOLVER use	Three-item perceptual measure	Interval	Taylor and Todd (1995)
IT acceptance	Whether SOLVER is used (and not subsequently rejected) during the task	Auditing software, Perceptual measure	Binary Interval	- Davis, Bargozzi and Warshaw (1989)
IT infusion	Number of functionalities within SOLVER used by subject	Examination of diskette Three-item perceptual measure	Ratio Interval	- None

*Variables manipulated via dichotomous treatments.

Chi-square tests were conducted to assess the goodness-of-fit between actual treatment manipulations and perceptual measures (averaged) of these manipulations. Three of the five treatments had chi-square values significant at the 0.05 level (see Table 4), indicating that these treatments did have the intended effects on subjects. Chi-squares for the other two treatments (i.e., incentive type and behavioral evaluation) were significant at the 0.10 level. This lack of fit was not of significant concern since model validation was performed using the perceptual measures only, which demonstrated adequate levels of reliability and validity (see section 3.3).

Table 4. Validation of Treatment Effects

Treatment variable	Pearson's chi-square	p-value (goodness-of-fit)
Incentive level	35.224*	0.006
Incentive type	19.294†	0.074
Behavioral evaluation	24.803†	0.090
Repeated contract	44.322*	0.001
Monitoring	18.713*	0.040

Note: Chi-square significant at 0.05 and 0.10 levels are denoted by * and † respectively.

Measuring IT usage, the dependent variable in this study, has been a topic of considerable debate among MIS researchers (Trice and Treacy 1988). IT usage may refer to the breadth of use (e.g., number of users utilizing the IT, number of tasks in which the IT is used) or depth of use (e.g., number of functions within the IT utilized by users, proportion of tasks in which IT is used). Rather than focusing on one of these dimensions, the current study views IT usage as a multidimensional construct consisting of both breadth and depth, captured respectively as IT acceptance and infusion. Both dimensions were measured using objective and perceptual measures in order to cross-validate usage data and in addition, examine the fit between these measures, since one recent study (Straub, Limayem and Karahanna-Evaristo 1995) provided evidence to the contrary.

Acceptance, defined in the implementation literature as potential users' decision to use or not use a IT (Cooper and Zmud 1990), was operationalized in this study as a binary variable referring to SOLVER usage (without subsequent rejection) or non-usage in performing the assigned task. It was measured objectively using an network auditing software called SofTrack and perceptually using a Likert-scaled measure on the post-treatment questionnaire. *Infusion*, defined as the extent to which IT is utilized, was operationalized as the number of correct functionalities within SOLVER utilized by subjects in performing the assigned task. An initial list of functionalities was developed based on guidelines in the users' manual for solving similar tasks, which was validated by examining the functionalities used by pilot test subjects who completed the task correctly. Irrelevant or incorrectly used functionalities were not considered and, therefore, this assessment captured "appropriateness" of IT use. Infusion was measured objectively by examining the diskette turned in by subjects, and perceptually via a multiple-item Likert-scaled measure. An additional check-in item was used as a cross-check, where the subject was provided with a list of SOLVER functionalities and asked to check those that he/she used during the task. Several spurious functionalities were included in this list to guard against possible random checking.

3.3 Instrument Validation

Initial versions of the pre-treatment and post-treatment questionnaires were constructed by randomly ordering items from different scales. All scale items were worded to relate specifically to SOLVER usage rather than to IT usage in general. This instrument was then subjected to a pilot test sample of 71 student subjects. Respondents were asked to complete each questionnaire and then comment on its length, wording, and instructions. This helped identify unclear or ambiguous items, which were then either reworded or eliminated. The remaining scales, consisting of three items per construct, were psychometrically evaluated for their reliabilities and construct validities using 132 subjects in the experimental study (22 subjects per treatment group).

Instrument validation was done via confirmatory factor analysis, performed using PLS-Graph, Version 2.91 (Chin and Frye 1994), a partial least squares software based on Lohmoller's (1989) PLSX program. PLS-Graph allows graphical specification of latent variables (theoretical constructs), manifest variables (measuring indicators), and their interrelationships, and estimates model parameters using an iterative ordinary least squares approach. The measurement model estimated by PLS is useful in validating research instruments, while the structural model enables model testing and comparison.

Cronbach alpha (internal consistency) was calculated for each scale from the matrix of inter-item correlations. The means, standard deviations, and Cronbach alphas are reported in Table 5. Nine of the eleven perceptual scales had Cronbach alphas greater than 0.8 (reliabilities of incentive type and behavioral evaluation were fairly close to that figure), attesting to the overall reliability of the research instrument.

The principal component factor model generated by PLS-Graph was used to examine construct validity for each scale. One rule of thumb for assessing construct validity is that each item should have a minimum factor loading of 0.6 on its hypothesized construct (for convergent validity) and less than 0.3 loading on all other constructs (for discriminant validity) (Kim and Mueller 1978); this criterion was met for all but three of a total of thirty items (see Table 5). Factor loadings ranged from 0.499 to 0.938, with several loadings exceeding 0.80. Nine of the eleven scales extracted over 70 percent of the scale variance, providing further evidence of the representativeness of these scale items.

Table 5. Scale Reliabilities and Validities (Perceptual Measures)

Scale	# of items	Mean	Std Dev (pooled)	Cronbach alpha	Factor loadings	Variance extracted
Incentive level	3	4.580	2.061	0.906	0.852, 0.903, 0.938	0.851
Incentive type	3	3.611	2.205	0.784	0.854, 0.499, 0.843	0.565
Monitoring	3	4.134	2.119	0.864	0.860, 0.920, 0.881	0.808
Behavioral evaluation	3	3.596	2.138	0.775	0.855, 0.590, 0.832	0.620
Repeated contract	3	2.843	2.177	0.867	0.937, 0.935, 0.888	0.837
Behavioral intention	3	5.328	1.683	0.893	0.889, 0.926, 0.911	0.844
Usefulness	3	6.004	1.298	0.842	0.774, 0.866, 0.790	0.804
Ease of use	3	4.626	1.763	0.805	0.684, 0.780, 0.562	0.698
Attitude	3	5.408	1.690	0.836	0.627, 0.761, 0.902	0.757
Perceived acceptance	3	4.088	2.234	0.831	0.851, 0.860, 0.635	0.732
Perceived infusion	3	4.982	2.146	0.818	0.895, 0.882, 0.935	0.711

Note: All items were measured on 7-point Likert scales, except perceived acceptance, which was measured in binary terms.

4. RESULTS AND DISCUSSION

Structural equation modeling (SEM) using partial least squares (PLS) technique was employed to test associations in the proposed model of IT usage, and to compare this model with TAM and an integrated usage model formed by combining TAM and PAM variables. Compared to traditional regression-based approaches, where causality is inferred purely from empirical data, the newer SEM-based approaches (e.g., LISREL, PLS) attempt to combine both abstract theoretical reasoning and empirical measurement in knowledge building/testing (Fornell 1989), and are becoming an increasingly popular methodology in most behavioral research (Loehlin 1987; Harris and Schaubroeck 1990).

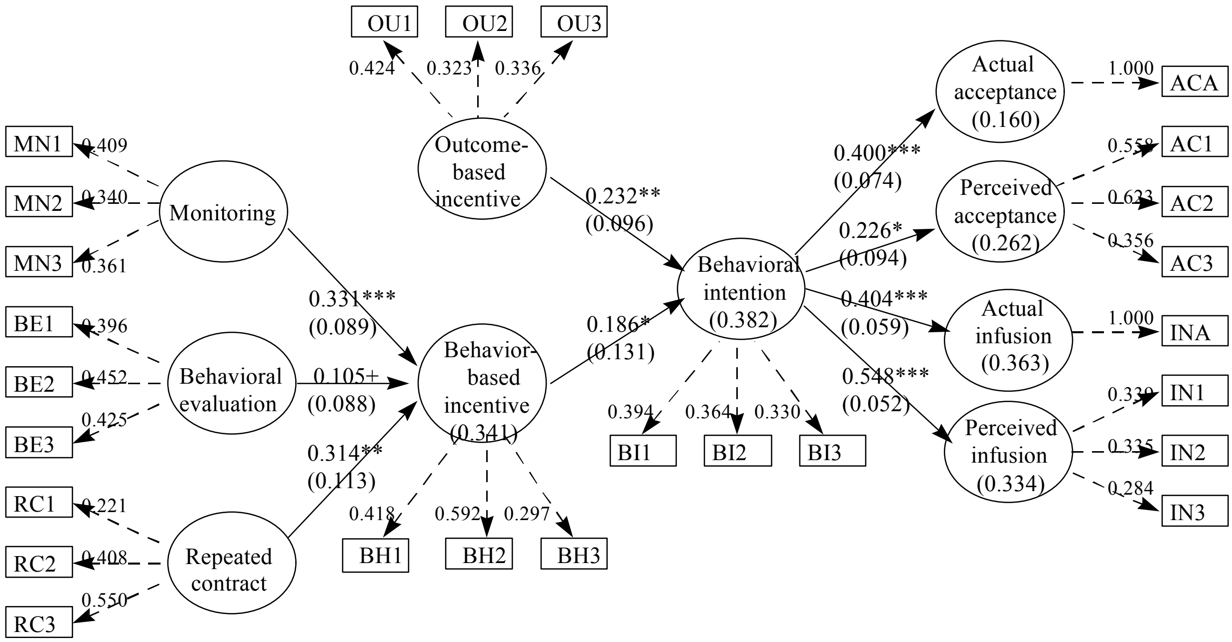
Though LISREL is the most popular SEM approach in behavioral research (e.g., Taylor and Todd 1995), PLS (Wold 1981) may be a more powerful alternative because of the minimal demands it places on residual distributions, measurement scales, and sample sizes. Unlike LISREL, PLS is distribution-free, i.e., it does not require data to be multivariate normal. PLS can be used with non-interval scaled data, requires a sample size significantly smaller than that required by LISREL, and is suited to handling models as large as 100 indicators (Fornell and Bookstein 1982). PLS is also less affected by multicollinearity because parameters are estimated in blocks separated from one another, so that bias in one parameter estimate is less likely to affect estimates of other parameters (Harris and Schaubroeck 1990). Most importantly, while factors-based LISREL is appropriate in areas where prior theory is strong and further theory testing and development is the goal, the component-based PLS is more suited to areas where the theory is weak or tentative (Fornell and Bookstein 1982). Given that in theory building in the area of incentives and control is in its formative stages and the limited sample size in the experimental study (132 subjects for thirteen variables), PLS was considered to be a more appropriate choice.

PLS analysis was performed for three models: PAM, TAM, and an integrated IT usage formed by combining PAM and TAM constructs within a TPB framework. Chin and Frye's PLS-Graph Version 2.91 was used for this purpose. Results of the analysis are presented in Figures 2, 3, and 4 respectively. In each model, scale items (manifest variables) were linked to the underlying constructs (latent variables) in reflective mode, since subjects' perception of constructs were believed to giving rise to their item responses. Both measurement and structural models are shown in Figure 2 (PAM) as an illustration of PLS, while only the structural models are depicted in Figures 3 and 4 for purposes of clarity. For each model, PLS-Graph generated path coefficients for all hypothesized paths and variance explained (R^2) for all dependent variables. Standard error and path significance were assessed using a bootstrapping option in PLS-Graph using the recommended sample size of 100.

4.1 Support for PAM

Empirical analysis of the path model hypothesized by PAM is presented in Figure 2, while the bivariate correlation between constructs are presented in Table 6. With the exception of the path from behavioral evaluation to behavior-based incentives, all path coefficients were found significant at the 0.05 level. Behavioral intention significantly predicted all four measures of IT usage, although the correlation and proportion of variance explained varied considerably across the four measures. The strongest correlations were observed for actual and perceived infusion (0.58 and 0.52 respectively), which explained 36 and 33 percent of the variance on these variables. This R^2 is roughly consistent with that reported by Sheppard, Hartwick and Warshaw's (1988) meta-analysis of 87 studies, and TAM-based studies by Davis, Bargozzi and Warshaw (1989) and by Taylor and Todd. However, the R^2 values were considerably less for acceptance and also differed markedly across its actual and perceived measures (0.16 and 0.26 respectively). Although these differences are partly diluted by the binary operationalization of acceptance measures, it is possible that in the presence of usage-related incentives, users may overestimate their level of IT acceptance, supporting Straub, Limayem and Karahanna-Evaristo's contention that perceived and actual measures of usage are not always interchangeable.

Other paths in Figure 2 provide overall support for PAM's hypotheses that incentives and control mechanisms are important predictors of IT usage. Outcome-based and behavior-based incentives respectively had 0.31 and 0.14 correlations with IT usage (averaged across the four usage measures). Together, the two incentive variables accounted for 38 percent of the variance in behavioral intention, and thereby had an indirect effect on IT usage. Control mechanisms such as monitoring and repeated contracts also had significant direct effects on behavior-based incentives, thus indirectly influencing behavioral intention and IT usage. The linkage between behavioral evaluation and behavior-based incentives was, however, not significant. This lack of association may be attributed to two reasons: subjects did not perceive relative and absolute behavior as being significantly



Note: Path significance: ***p < 0.001, ** p < 0.01, *p < 0.05, +p < 0.10. The following transformations were employed: OUn = (1Tn - 4) * ILn if lTn > 4 and 0 otherwise, BHn = (4 - lTn) * ILn if ITn < 4 and 0 otherwise.

Figure 2. Path Coefficients in Principal-Agent Model

different (as indicated by the relatively low goodness-of-fit between this treatment manipulation and its perception), or such difference did not cause any significant difference on intention and usage.[6] Table 6 indicates that 38 of the 45 bivariate correlations among model variables were less than 0.5, providing greater confidence to the results of the PLS analysis.

4.2 Comparison with TAM

As a second stage of analysis, the explanatory power of PAM was compared with that of an established model of IT usage (TAM) and an integrated model formed by synthesizing PAM and TAM variables within the theory of planned behavior (TPB) framework (Ajzen 1991). Parameter estimates for TAM and the integrated model are presented in Figure 3 and 4 respectively, while the explanatory power of the three models, as indicated by R^2 values on intention and usage variables, are summarized in Table 7.

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[6]Post-treatment discussion with a few subjects revealed that many subjects in the behavior-based groups felt that they had to use SOLVER and obtain the right result in order to receive the highest possible credit, irrespective of whether they were evaluated on relative or absolute scales.

Table 6. Bivariate Correlations among Model Variables

	BIP	ACA	ACP	ILP	ITP	MNP	BEP	RCP	INA	INP
BIP	1.000									
ACA	0.399	1.000								
ACP	0.512	0.461	1.000							
ILP	0.229	0.213	0.412	1.000						
ITP	0.044	-0.162	-0.115	-0.184	1.000					
MNP	-0.169	-0.115	-0.145	-0.290	0.340	1.000				
BEP	-0.153	-0.115	-0.016	0.228	-0.166	-0.158	1.000			
RCP	-0.022	-0.148	-0.078	-0.086	0.101	-0.065	-0.081	1.000		
INA	0.578	0.821	0.551	0.300	-0.146	-0.126	-0.158	-0.150	1.000	
INP	0.524	0.594	0.651	0.326	-0.140	-0.281	0.029	0.057	0.506	1.000

Legend: BIP: behavioral intention; ACA: actual acceptance; ACP: perceived acceptance; ILP: incentive level; ITP: incentive type; MNP: monitoring; BEP: behavioral evaluation; RCP: repeated contract; INA: actual infusion; INP: perceived infusion

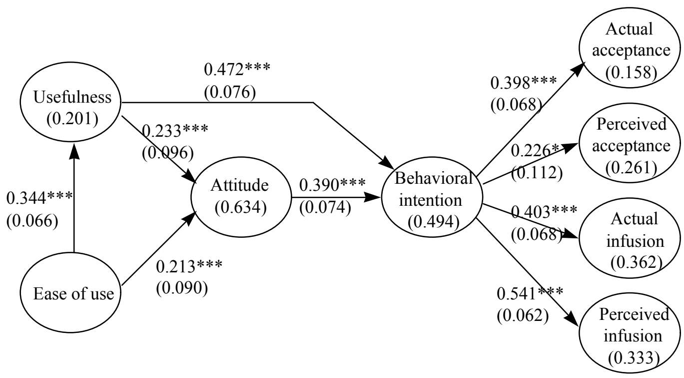

Figure 3. Path Coefficients in Technology Acceptance Model

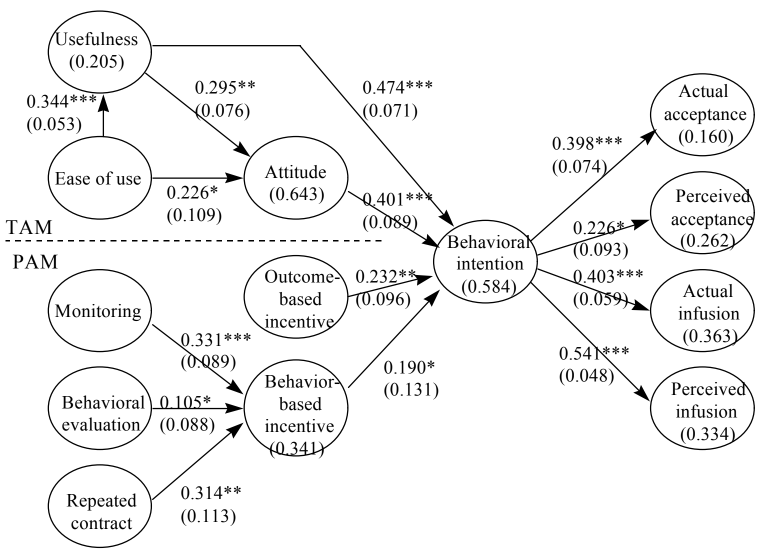

Figure 4. Synthesis of TAM and PAM Using the TPB Framework

Table 7. Explanatory Power of PAM, TAM, and the Integrated Model of IT Usage

Dependent variable	PAM	TAM	Integrated Model
Behavioral intention	0.382	0.494	0.584
Actual acceptance	0.160	0.159	0.160
Perceived acceptance	0.262	0.261	0.262
Actual infusion	0.363	0.362	0.363
Perceived infusion	0.334	0.333	0.334

TPB is considered to be a generalization of TAM, because in addition to user attitudes, it also includes subjective norms and behavioral control as determinants of individual usage behavior (Mathieson 1991; Taylor and Todd 1995). However, being a general model of human behavior, TPB does not specify the exact set of normative or control beliefs that determine subjective norm or behavioral control. In organizational contexts, managers represent a powerful referent group, whose influences on intraorganizational behavior should be realized via TPB's subjective norm construct. Since incentives and control are important dimensions of managerial influence, they can be viewed as normative beliefs indirectly affecting intention and usage. Note here that since PAM's goal incongruence is the inverse of TAM's behavioral intention, behavioral intention in TPB provides a link between PAM and TAM constructs. Also, since PAM has no direct or indirect implications regarding behavioral control, this construct is left out of further analysis.

The role of subjective norm as a determinant of IT usage is not yet established in the implementation literature. Davis, Bargozzi and Warshaw (1989) and Mathieson reported that, while TAM accounted for 35 percent of the variance in IT usage, addition of subjective norm did not add any additional explanatory power to the dependent variable. This inconclusive result may be attributed to several reasons. First, in the experimental settings employed by Davis, Bargozzi and Warshaw (1989) and Mathieson, there were no real consequences associated with subjects' behavior and therefore subjects had little external pressure to perform the intended behavior (Davis, Bargozzi and Warshaw 1992). In a setting where reward structures are associated with the intended behavior (e.g., within organizations), subjective norm may be expected to have a greater impact on intention and usage (Taylor and Todd 1995). This is partly supported by Hartwick and Barki (1994), who found that mandated and voluntary use resulted in different relative impacts for attitude and subjective norms. Second, in TPB, the different perceptual beliefs constituting the subjective norm construct are combined into an unidimensional whole via a weighted summation. If these individual belief sets have opposite effects on subjective norm, a summation may cancel out their mutual effects and the monolithic measure may not be an accurate representation of subjective norm. Third, while belief structures related to attitude (i.e., usefulness and ease of use) have been well developed, refined, and validated by Davis (1989), little effort has been devoted to identifying a stable set of beliefs relevant to subjective norm, leading to atheoretical and potentially inaccurate measures for this construct.

Given these limitations, Taylor and Todd suggested a broader exploration of the determinants of subjective norm beyond those held by traditional intention-based models, and recommended examining the effects of these determinants separately, as opposed to combining them into a monolithic construct. The current study represents an attempt toward that goal by proposing managerial incentives and control as normative beliefs contributing to subjective norm in organizational settings.

A comparison of the explanatory power of the three models (see Table 7) indicates that behavioral intention (goal congruence) accounted for 16 percent of the variance in actual acceptance, 26 percent in perceived acceptance, 36 percent in actual infusion, and 33 percent in perceived infusion in all three models. This was expected since intention was the only determinant of IT usage in all three models. More substantive in this context were the differential effects of the preceding variables on intention across the three models. While incentives and control mechanisms in PAM explained 38 percent of the variance in behavioral intention, attitudinal variables in TAM explained 49 percent of the variance, and PAM and TAM variables combined in the integrated model explained 58 percent. Addition of incentive and control variables therefore resulted in an increase in explanatory power of 9 percent in behavioral intention over and above the TAM variables (i.e., usefulness, ease of use, and attitude). Also, by specifically focusing on managerial incentives and control, the usage model becomes more relevant to managers interested in formulating strategies for effective implementation of IT within their organizations.

5. CONTRIBUTIONS TO MIS RESEARCH

The epistemological contribution of this study to IT implementation research is in theorizing the role of managerial incentives and control in influencing intraorganizational IT usage. Organizational studies have found managerial influences to be important determinants of behavioral intention and usage (Leonard-Barton and Deschamps 1989), which is ignored in TAM due to the model's sole focus on attitudinal factors (Fichman 1992). PAM can therefore be viewed as complementing TAM while generalizing IT usage research from personal use to organizational settings. A key distinction between the two settings may be the voluntariness assumption. Although IT usage in personal-use settings is entirely voluntary, this is less so in organizational settings, where users are expected to behave in accordance with the management's goals.[7] As such, incentives and control mechanisms are intended to overcome users' involuntariness regarding IT usage in such settings. It is possible that although voluntary usage (in personal use settings) is determined primarily by individual attitudes (as suggested by TAM), involuntary usage in organizational setting may be predicted jointly by both attitudes and subjective norm (defined as a collection of incentive and control variables), as observed in this study. PAM can therefore provide valuable insights on involuntary usage, which to date has received little attention in IT usage research.

The goal to integrate micro-level individual factors and macro-level managerial factors within a common framework has been urged repeatedly in the implementation literature (DeSanctis 1984). Successful implementation of IT in organizations requires not only positive beliefs, attitudes, and intentions on the part of users, but also appropriate incentives, strategies, and actions on the management's part. While prior usage models (e.g., TAM) were primarily concerned with individual factors, PAM provides a tool to integrate individual factors (e.g., intentions) and managerial factors (e.g., incentives, control), and thus may provide a comprehensive explanation of IT usage.

A third contribution of PAM is that it provides a bridge between the traditionally segregated economic and political schools of thought in MIS research. Although the political conflict stream of MIS research holds that organizational members may indulge in opportunistic and subversive behavior in order to protect their own interests (e.g., Markus 1983; Kling and Iacono 1984), such behavior has been difficult to justify from a rationalistic standpoint. By attributing political behavior to goal incongruence among organizational members, PAM provides a rationalistic lens to interpret political behavior and suggests organizational mechanisms (e.g., incentives and control) that can help mitigate problems associated with such behavior.

6. LIMITATIONS AND FURTHER RESEARCH

This study suffers from several theoretical and methodological limitations. First, laboratory experiments, by their very nature, tend to limit the external validity (generalizability) of their results. Chapnis (1983) notes that such experiments can examine only a small number of variables, develop models that are at best rough and approximate models of reality, and produce results that may not be adequately generalizable to other populations, settings, and treatments. Given the emphasis in this study on causality over generalizability, it was restricted to a laboratory experiment. Future research may replicate this study in field settings to improve the generalizability of these findings. Such replication may also take into account the effect of negative incentives (e.g., threats, disincentives) that was not considered in this study.

Second, the proposed model of IT usage was concerned mostly with the agent (user) side of the principal-agent problem. It examined what incentives and control mechanisms are effective in motivating user behavior and why, but ignored the management's costs in designing and implementing these incentives. A complete understanding of intraorganizational IT usage

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[7]A three-item perceptual voluntariness measure (adapted from Moore and Benbasat 1991) indicated that users considered SOLVER usage in this study to be involuntary.

would, however, require a thorough examination of both sides of the problem. Future research may target the principal's problem to identify the management's cost-minimizing choice of incentives and control structures, given problems of goal incongruence and information asymmetry.

Third, most applications of principal-agent research to the study of organizations have been restricted to theoretical exposition of propositions, rather than empirical testing of these propositions (e.g., Eisenhardt 1989; Gurbaxani and Kemerer 1990). Part of the problem associated with testing these propositions may be attributed to difficulties in operationalizing economic constructs such as risk aversion, information asymmetry, and the like. Future studies may focus on developing instruments for measuring these constructs appropriately.

Finally, the principal-agent model is a generic economic tool that can be potentially applied to a large number of MIS management problems characterized by goal incongruence, risk aversion, and information asymmetry (Gurbaxani and Kemerer 1990). Future research efforts may be directed at identifying research areas in MIS that can potentially benefit from the use of this model.

To conclude, the findings of this study indicate that incentives and control (e.g., monitoring, repeated contracts) can indeed motivate individual IT usage behavior within organizations. Empirical data provides support for TAM; however, it also demonstrates that explanation of IT usage can be enhanced by about 9 percent by incorporating incentives and control variables as additional predictors of intention. Inclusion of these variables is similar to adding TPB's subjective norm construct and, therefore, TPB provides an effective framework to integrate PAM and TAM variables.

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APPENDIX[8]

*IL1. Compared to other students in the class, I will receive less bonus points for doing this assignment.
*IL2. Others in the class are being rewarded more than me for doing the same assignment.
*IL3. I think that I am receiving less reward than other students in the class for the same assignment.

IT1. The bonus points I will receive from this assignment depend not on my use of SOLVER, but rather on my completing this assignment.
IT2. The bonus points I will receive from this assignment depend on my recommended solution in the assignment.
*IT3. The bonus points I will receive from this assignment are based on how well I use SOLVER, rather than on my completing this assignment.

MN1. I believe that my computer use is being monitored.
MN2. Some network software is monitoring my use or non-use of SOLVER.
*MN3. I think that I am not being monitored.

BE1. The bonus points I will receive in this assignment depend on how well I use SOLVER compared to others in my group.
*BE2. The bonus points I receive from this assignment depends on my individual use of SOLVER, irrespective of others' use or non-use of SOLVER.
BE3. My use of SOLVER in this assignment will be evaluated relative to others in my group.

RC1. If I do well in the current assignment, I will receive have a second bonus assignment where I can earn five more extra-credit points.
RC2. I can possibly get a second extra-credit assignment.
RC3. My performance in the current assignment will determine whether I can get a second extra-credit assignment.

US1. I think that using SOLVER will help me complete the assignment.
US2. In my opinion, SOLVER is a useful tool for doing assignments of this type.
US3. I think that I will find SOLVER useful in completing this assignment.

EU1. Using SOLVER will be easy for me.
EU2. I can easily get SOLVER to do whatever I want it to do.
*EU3. I think SOLVER is too complex to use.

AT1. Using SOLVER is a ______ idea for this assignment.
AT2. I ____ the idea of using SOLVER for this assignment.
*AT3. I think using SOLVER is a foolish idea for this assignment.

BI1. I intend using SOLVER for doing this assignment.
BI2. Compared to other methods, I prefer using SOLVER for this assignment.
BI3. I would rather use solver than any other methods in doing this assignment.

*AC1. I used SOLVER for doing this assignment (circle one): Yes / No
*AC2. I tried using SOLVER, but could not get it to work, and therefore switched to a different method: Yes / No
AC3. The amount of time I spent using SOLVER is approximately: _______ minutes.

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[8] All perceptual items were measured on a 7-point Likert scale from "extremely disagree" to "extremely agree." Reverse-coded items are indicated by asterisk. Acceptance and infusion were measured after the treatment; all other variables were measured prior to the treatment. Legend: IL: incentive level, IT: incentive type, MN: monitoring, BE: behavioral evaluation type, RC: repeated contract, US: usefulness, EU: ease of use, AT: attitude, SN: subjective norm, BI: behavioral intention, AC: acceptance, IN: infusion.

IN1. I made appropriate use of SOLVER in completing this assignment.
IN2. I used SOLVER correctly to do the assignment.
IN3. I used most of the functionalities of SOLVER in doing this assignment.
IN4. The steps I took while doing this assignment are (check as many as applicable):

[ ] Specifying values in the Set Target Cell box
[ ] Maximizing value in one target cell
[ ] Maximizing values in multiple target cells
[ ] Clicking the Reset All button
[ ] Minimizing values in multiple target cells
[ ] Setting up a range of cells that can be changed
[ ] Specifying which cells cannot be changed
[ ] Adding constraints
[ ] Setting integer constraints
[ ] Setting values in the Goal Seek box
[ ] Selecting the Best Estimate option
[ ] Using the Merge option in Scenario Manager
[ ] Using the Macro facility within SOLVER
[ ] Setting up Filters to be used
[ ] Setting up Tracer precedents and dependents