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Examining Multiple Dimensions of Task Technology Fit

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ABSTRACT

Investigating the fit of an information technology to a user's task, known as task-technology fit (TTF), is a frequent focus of HCI/MIS research. In such research, "fit as moderation", one of Venkatraman's (1989) six conceptualizations of fit, is common. This conceptualization assumes two variables, e.g., task and technology, and an outcome variable. Task and technology, however, have multiple dimensions that should be considered when investigating fit. We examine three methods HCI/MIS researchers have used for augmenting the fit as moderation conceptualization for multiple dimensions. We propose and test a new method involving a single PLS model capturing the multiple dimensions of fit, which is more consistent with Venkatraman's (1989) original conceptualization and statistical model for fit as moderation than those currently in the literature. Our method as compared against one method in the literature, using a separate model for each dimension, works at least as well.

Keywords

Task-technology fit, fit as moderation, fit as profile deviation, PLS.

INTRODUCTION

Human-computer interaction (HCI) research, as well as much of MIS research, addresses the general question of designing information technologies (IT) to fit the needs of individuals performing various tasks using those technologies. As a sub-discipline of HCI/MIS research, task-technology fit (TTF) research examines methods for conceptualizing and measuring the extent to which a particular IT fits a particular task. In this paper, we investigate methods for conceptualizing and measuring fit along multiple dimensions.

We examine three methods for conceptualizing and measuring multi-dimensional fit currently in the MIS literature: (1) Fit as profile deviation (Venkatraman 1989; Zigurs and Buckland 1998; Zigurs, Buckland, Connolly and Wilson 1999), (2) Fit as moderation, assessed by users via a questionnaire (Goodhue 1995; Goodhue and Thompson 1995; Venkatraman 1989), and (3) Fit as moderation, assessed via separate model estimations for each fit dimension (Dishaw and Strong 1998; Venkatraman 1989). Each of these, however, has disadvantages as a method for conceptualizing and measuring multi-dimensional fit. We then propose and test a new method for conceptualizing and measuring multi-dimensional fit, Fit as moderation assessed via a single PLS model.

TASK - TECHNOLOGY FIT MODELS

The ability of IT to support a task is expressed by the formal construct known as Task-Technology Fit (TTF), a well-known construct in the MIS literature. A core thesis of TTF models, as summarized in Dishaw and Strong (1998), is that "technology, e.g., software, will be used if, and only if, the functions available to the user support (fit) the activities of the user. A software function supports an activity if it facilitates that activity. Rational, experienced users will choose those tools and methods that enable them to complete the task with the greatest net benefit. Software that does not offer sufficient advantage will not be used." Models developed around the TTF construct, called TTF models, have taken a variety of forms.

Fit as Moderation

To bring some clarity to research using the concept of fit, Venkatraman (1989) described six different perspectives for conceptualizing fit: fit as moderation, fit as mediation, fit as matching, fit as gestalts, fit as profile deviation, and fit as covariation. Each of these conceptualizations has corresponding methods for assessing fit according to that conceptualization. While his six perspectives are presented in the context of strategy literature, e.g., the fit between organizational strategy and the organizational environment, they apply equally well to the HCI/MIS literature focusing on the fit between IT and tasks.

Fit as moderation is a common conceptualization of fit in the MIS/HCI literature. In this conceptualization, IT is a moderator that affects (hopefully improves) the resulting outcome measure, performance of a task by an individual or utilization of the technology by an individual (see Figure 1). That is, according to the fit as moderation model, the use of IT serves as an enabler of better task performance. In the general forms of the TTF model shown in Figures 1-3, we list both outcome measures (dependent variables), IT utilization and individual performance, that are found in the literature. In the study reported in this paper, we employ IT utilization as the dependent variable.

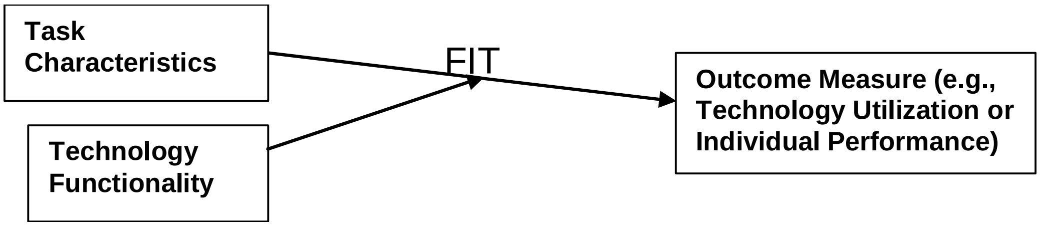

Figure 1. Conceptualization of Task-Technology Fit as Moderation

The statistical model corresponding to the fit as moderation conceptualization has two direct effects and an interaction effect (Venkatraman 1989). Specifically, the statistical model for estimation corresponding to Figure 1 is a model with task and technology main effects and a task-technology interaction effect, each of which directly affects an outcome variable, as shown in Figure 2.

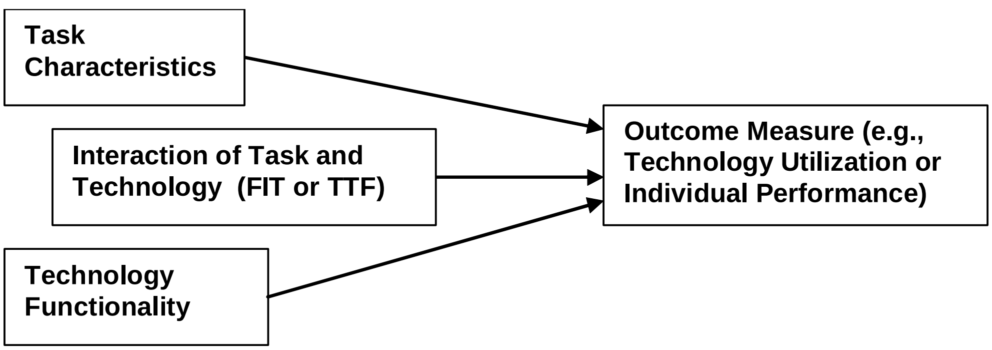

Figure 2. Statistical Model for Task-Technology Fit as Moderation

Of Venkatraman's (1989) six perspectives on fit, the first three, including fit as moderation, are bivariate forms that consider fit between two variables, e.g., task and technology or strategy and environment. The last three, including fit as profile deviation, are appropriate for conceptualizing and measuring fit among a larger set of variables (Venkatraman 1989). Venkatraman, however, does not specifically address multiple dimensions of the bivariate fit variables. In terms of both conceptualization and measurement, task and technology or strategy and environment are likely to be multi-dimensional constructs. As a result, HCI/MIS researchers have taken at least three different approaches to handling the multi-dimensional nature of task-technology fit.

Multiple Fit Dimensions via Fit as Profile Deviation

In contrast to fit as moderation, fit as profile deviation explicitly handles multiple variables (Venkatraman 1989). According to this conceptualization of fit, a task is defined by a set of dimensions. For each set of task dimensions, there is a proscribed set of technology functions that form the ideal profile or best fit for that task. The ideal technology profile for a task is expected to produce the best performance for that task. The conceptualization of fit as profile deviation has been used in the group decision support systems (GDSS) literature (Zigurs and Buckland 1998). Multiple dimensions are handled by treating multiple GDSS task dimensions together as a set, and similarly for multiple GDSS technology dimensions. Treating multiple dimensions by conceptualizing fit as profile deviation works well in the GDSS context because there is some agreement on the characteristics of GDSS tasks, the types of technology functionality that should be available in a GDSS tool, and what types of tasks each technology set is designed to support.

Multiple Fit Dimensions via Fit Evaluations by Users

Goodhue (1995) and Goodhue and Thompson (1995) use the fit as moderation conceptualization as a basis for a stream of research that develops a measure of fit in the form of a questionnaire of users. This questionnaire is operationalized for the task domain of "using quantitative information in managerial tasks" and includes twelve dimensions of fit of information to that task, with each fit dimension operationalized with several questionnaire items (Goodhue 1995). From the perspective of Figure 2, Goodhue's (1995) approach inserts a mediator variable, fit, that captures the effects of task characteristics, technology functionality, and the interaction of task and technology. Using this conceptualization, fit is measured via a questionnaire of users that captures the multiple dimensions of fit. This fit variable can then be used to test its effects on utilization of the technology and on individual performance (Goodhue and Thompson 1995).

Goodhue's method transforms fit from a conceptualization as a latent unobserved variable to a conceptualization as a variable that can be directly measured via questionnaire. With this transformation, multiple dimensions of fit are relatively easy to handle. The researcher must still provide a theoretical rationale for the dimensions measured and must develop a measurement instrument with multiple measures per dimension.

Multiple Fit Dimensions via Multiple Statistical Models

Dishaw and Strong (1998) also use the fit as moderation conceptualization described by Venkatraman (1989). Their statistical model is the same as Figure 2, estimated with a regression model. Their context is software maintenance support tools used by software maintainers. They model two dimensions of fit, production fit and coordination fit, based on the two different types of technology functionality in support tools, functionality to support the program design or maintenance task, which is called production functionality, and functionality to support coordination of that individual task with others in the software development environment, called coordination technology (Henderson and Cooprider 1990). To estimate fit along these two dimensions, Dishaw and Strong (1998) use two separate regression models. One model includes production functionality in the technology, characteristics of production tasks, and production fit, which is the interaction of production technology with production tasks. The second model is similar, but focuses on coordination functionality, coordination tasks, and coordination fit.

In their more recent work, Dishaw and Strong have explored the addition of other explanatory variables to TTF models. In doing so, they have continued with the fit as moderation conceptualization, but have focused on the single dimension of production fit. For example, they investigated the addition of TAM variables to TTF (Dishaw and Strong 1999), task and tool experience variables (Dishaw and Strong 2003), and self-efficacy (Strong, Dishaw and Bandy 2005). In these studies, they have also switched from using multiple regression to structural equation models (AMOS), and most recently to PLS, and have generalized from the software maintenance context to any individual support tool designed to support problem-solving or modeling tasks.

PROPOSED MULTI-DIMENSIONAL TTF MODEL

As described in the literature review, previous researchers have developed several methods for handling the multiple dimensions of fit. The three methods discussed above are to use fit as profile deviation rather than fit as moderation because it handles multiple dimensions explicitly, to introduce a fit variable that can be directly measured via a questionnaire that covers multiple dimensions of fit, or to use multiple fit estimation models, one for each fit dimension. While all these methods work, none of them capture the essence of multi-dimensional fit as moderation. In this paper, we explore another method of handling multiple dimensions of fit. We retain Venkatraman's (1989) original conceptualization of fit as moderation as in Dishaw and Strong (1998), but explore the estimation of multiple dimensions of fit within a single PLS model.

General Form of a Multi-Dimensional Fit as Moderation Model

The general form of a multi-dimensional fit as moderation model is an extension of Figures 1 and 2. For the conceptual model in Figure 1, the task characteristics and technology functionality variables each could have multiple dimensions, resulting in multiple dimensions for fit. For the statistical model in Figure 2, it becomes the general model shown in Figure 3.

Context for a Multi-Dimensional Fit as Moderation Model

A key difficulty with TTF models is that they must be operationalized in a specific context. That is, the task and technology must be specified. This contrasts with the Technology Acceptance Model (TAM) which has general variables, i.e., perceived usefulness, perceived ease of use, and intention to use, that have been operationalized in a way that applies to many contexts, or can be tailored to a specific context with few changes to question wording (Davis 1989). For TTF models, such a general operationalization is not yet available. For example, Goodhue's (1995) TTF model is operationalized for the task of managerial use of quantitative data and the technology of quantitative data. While this is a relatively broad context, it differs substantially from the software maintenance tasks and tools used as the context for Dishaw and Strong's (1998) TTF model.

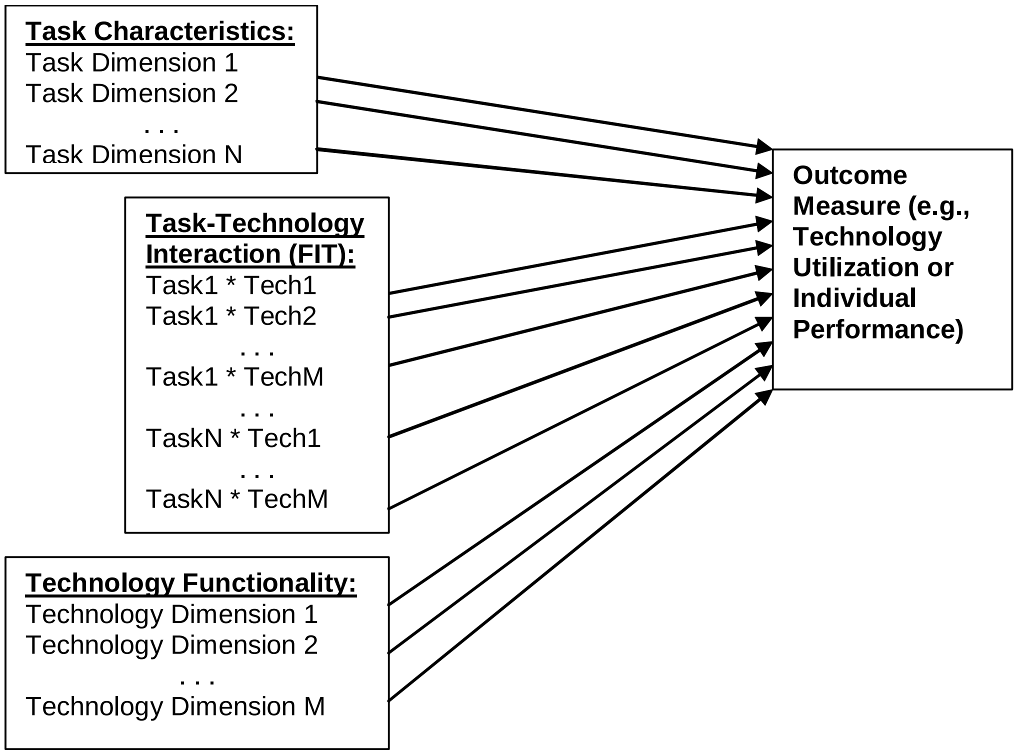

Figure 3. Statistical Model for Multi-Dimensional Task-Technology Fit as Moderation

Although the context must be specified for TTF models, the context can be fairly broad or quite narrow. For example, Dishaw and Strong (1998) specified a relatively narrow context, software maintain tasks and tools. Since then, they have gone back to the problem-solving literature, and have generalized their questionnaire items to provide broad coverage in their TTF questionnaire items for problem-solving tasks and IT tools that support such tasks. We use their generalized questionnaire items (Dishaw, Strong and Bandy 2001; Strong et al. 2005). While their operationalization does not cover all situations, e.g., it probably does not cover Goodhue's (1995) context of data use by managers, it does cover most software tools for individual problem-solving and productivity tasks. Below we present some background on the task and technology models used in this study, and their grounding in Dishaw and Strong's task and technology context.

Dishaw and Strong's initial task model (1998) is based on the major maintenance task activities of planning, knowledge building, diagnosis, and modification, identified during protocol analysis sessions of working maintainers (Vessey 1985, 1986). The first two activities involve understanding the problem, the third is diagnosing what needs to be done, while the last one is the actual program transformation activity. Because Vessey's work is well grounded in the problem solving and cognitive science literature, this task model is appropriate for more general problem-solving tasks, not just software maintenance tasks (Vessey 1986; Dishaw et al. 2001). Problem understanding and problem diagnosis are the two dimensions of the problem-solving task, i.e., the two task characteristics, used in this study.

Dishaw and Strong's initial technology model (1998) is based on the Henderson and Cooprider (1990) Functional Case Technology Model (FCTM), which provides a description of the basic functions present in design support software (CASE). This technology model is grounded in the literature on IT support functionality, and thus is appropriate for IT support tools beyond those designed for software maintenance. The functions that support an individual programmer developing or changing software include representation, analysis, and transformation functionality. These are the three underlying dimensions of production functionality mentioned earlier in our discussion of production fit. In this paper, we focus on the analysis functionality dimension of support technology.

Following from these task and technology models, we posit multiple possible fit dimensions or combinations as shown in Figure 4. Stated simply, the Understanding activity (or task characteristic) is supported by Analysis and Representation functionalities in the technology. The Diagnosis activity is also supported by these functionalities as well. In this paper, we are investigating our proposed multi-dimensional fit analysis method on only a portion of a full multi-dimensional fit model to assess its feasibility before doing an analysis of the complete model. Specifically, we test our multi-dimensional fit model using the first column in Figure 4 (the shaded area), that is, we test the fit of the support provided by the Analysis functionality of tools for both Understanding and Diagnosis task activities.

	Production Technology Functionalities	
Production Task Activities	Analysis Functionality	Representation Functionality
Problem Understanding	A/U Fit	R/U Fit
Problem Diagnosis	A/D Fit	R/D Fit

Figure 4. Multiple Dimensions of Fit

Dependent variable

In some TTF studies, the dependent variable in the models of fit is performance, e.g, (Goodhue and Thompson 1995). Dishaw and Strong (1998, 1999, 2003), however, focus on the performance antecedent, tool usage, as the dependent variable, which is most appropriate when the use of the tools is voluntary, as it was in their software maintenance context. This allowed them to consider a dependent variable that is closer, from the perspective of the causal chain, to the independent variable fit. This research also employs tool usage as the dependent variable.

RESEARCH METHOD

Data were collected by questionnaire. The questionnaire items for task and technology constructs were originally developed and tested by Dishaw and Strong (1998) in the software maintenance context, but since generalized and tested in the general problem solving context (Dishaw et al. 2001; Strong et al. 2005). From their task sub-constructs, we chose diagnosis and understanding as the critical activities for our modeling and problem-solving context. From their technology sub-constructs, we chose analysis functionality. Each of these three dimensions, diagnosis, understanding, and analysis, are measured with three questionnaire items. The three technology utilization items for the outcome measure, taken from Dishaw et al. (2001), ask users to report the extent of their use of analysis functionality. Because Fit is an interaction, it is not collected via questionnaire. An illustrative subset of the items appears in the appendix below.

The subjects are 220 business students from eleven different courses in operations management, information systems, and statistical analysis. The tools include Microsoft Access, SPSS, Microsoft Project, ProModel, or a CASE tool that students may choose to use for modeling and problem-solving assignments in these courses. These assignments were the last major project in each course. Within each group (course) all students completed the same assignment. The students completed the questionnaire after completing their assignment. Since an ANOVA test of the independent variables against the course revealed no significant differences among courses, we aggregated the data across courses.

Partial least squares (PLS-Graph version 3.0 build 1126) was used to perform the analysis because it is better than Structural Equation Modeling (using AMOS) for small sample sizes and for studies in which theory is still being developed (Chin and Gopal 1995; Chin, Marcolin and Newsted 1996; Wixom and Watson 2001). The model tested in this paper includes two latent fit variables, the fit between the Understanding task activity and Analysis functionality in the software (A/U Fit) and the fit between the Diagnosis task activity and Analysis functionality in the software (A/D Fit), which capture the interactions of the underlying dimensions of task and technology. Because PLS requires indicators for every latent variable, including interactions, nine indicators of fit are formed from the interactions of the three task and three technology indicators, for each fit dimension. This is the method recommended for modeling interaction latent variables in PLS (Chin et al. 1996).

To test whether multiple fit dimensions in a TTF model provide additional predictive power, we test the following three models.

1. Model 1a: Single dimension Fit model with Diagnosis Task Activity, Analysis Technology Functionality, and Analysis-Diagnosis Fit (see Figure 5).

2. Model 1b: Single dimension Fit model with Understanding Task Activity, Analysis Technology Functionality, and Analysis-Understanding Fit (see Figure 6).

3. Model 2: Multiple dimension Fit model with Diagnosis and Understanding Task Activities, Analysis Technology Functionality, Analysis-Diagnosis Fit and Analysis-Understanding Fit (see Figure 7).

To test the change in models from Model 1a or 1b to Model 2, it is appropriate to test the significance of the change in the F-statistic between models. PLS-Graph does not provide a direct calculation of the significance of the change of the F statistic. A hierarchical regression using the latent variable scores produced by PLS will provide this test statistic directly because our models are simple path models that do not have indirect paths. Complex path models, i.e., those with indirect paths, require the use of a pseudo F test as described by Mathieson, Peacock, and Chin. (2001). The latent variable scores, by case, obtained as part of the PLS output, serve as data in the SPSS regression. In our test, we designated model one as block one in the regression and the additional variables as block 2. The results of comparing the two models are shown below in Tables 4 and 5.

RESULTS AND DISCUSSION

Findings for Models 1a and 1b: The Single-Dimensional Fit Models

Figure 5 and Table 1 show the PLS statistics for Model 1a. These results for the first single-dimension TTF model are consistent with previously published results, e.g., Strong et al. (2005). As expected the effect of fit on utilization is strong and very significant. The task and technology variables impact utilization weakly, if at all. This is also expected because the effect should be through fit, not directly from task and technology characteristics. The R^2 for Model 1a is 0.341, which is in the same range as typical values from TAM and TTF models (Dishaw and Strong 1999; Strong et al. 2005).

Figure 6 and Table 2 show the statistics for Model 1b. These results for the second single dimension TTF model are similar to the results for Model 1a, that is, the effect of fit on utilization is strong and very significant and the task and technology variables impact utilization only weakly. The R^2 for Model 1a is 0.391, slightly higher than that for Model 1a.

Findings for Model 2: The Multi-Dimensional Fit Model

Figure 7 and Table 3 show the statistics for Model 2. Model 2, the multi-dimensional fit model, shows the effects of combining Model 1a and Model 1b. The R^2 for the resulting model is 0.419, higher than either of the single-dimension models.

In the independently estimated single-dimension models, A/D fit and A/U fit show strong (0.438 and 0.537) and significant (p=0.002 and p=0.0005) paths to utilization. In Model 2, both fit paths are still fairly strong (0.382 and 0.279), but are weaker than in the individual models. In addition, their significance is weaker (p=0.028 and p=0.123), that is, the path from A/D fit is significant, but that from A/U is not. This result requires further investigation, but is most likely due to co-linearity between the fit variables. Because A/U fit is not significant, the effect of the Understanding activity on utilization is stronger in the combined model (p=0.075 vs. p=0.136). Thus, understanding seems to be contributing what is different with the addition of the Understanding activity and A/U fit to the model.

Overall, our analysis clearly shows that the use of multiple fit dimensions improves the overall performance of the model (R^2 is 0.419 vs. R^2 of 0.341 and 0.391 for the individual models). The statistical support for this improvement is presented in the next section.

Comparison of Models 1a and 1b to Model 2

To test the significance of adding second task and fit dimension variables to Model 2, we use hierarchical regression using the PLS output. The addition of A/U fit and Understanding to Model 1a improves the model R^2 by 0.08, which is a significant improvement (see Table 4). The addition of A/D fit and Diagnosis to Model 1b improves the model R^2 by 0.03, also a significant improvement (see Table 5).

The results in Tables 4 and 5 essentially compare the approach of Dishaw and Strong (1998) to assessing multiple dimensions of fit using the fit as moderation conceptualization by testing independent models for each dimension to our new proposed approach to developing and testing a multi-dimensional approach to fit as moderation within a single model. Our findings indicate advantages to both approaches. Overall, the single model containing multiple dimensions of fit` provides better explanatory power for the outcome variable, tool utilization. The independently estimated single-dimension models, however, provide a better understanding of the effects of each dimension individually.

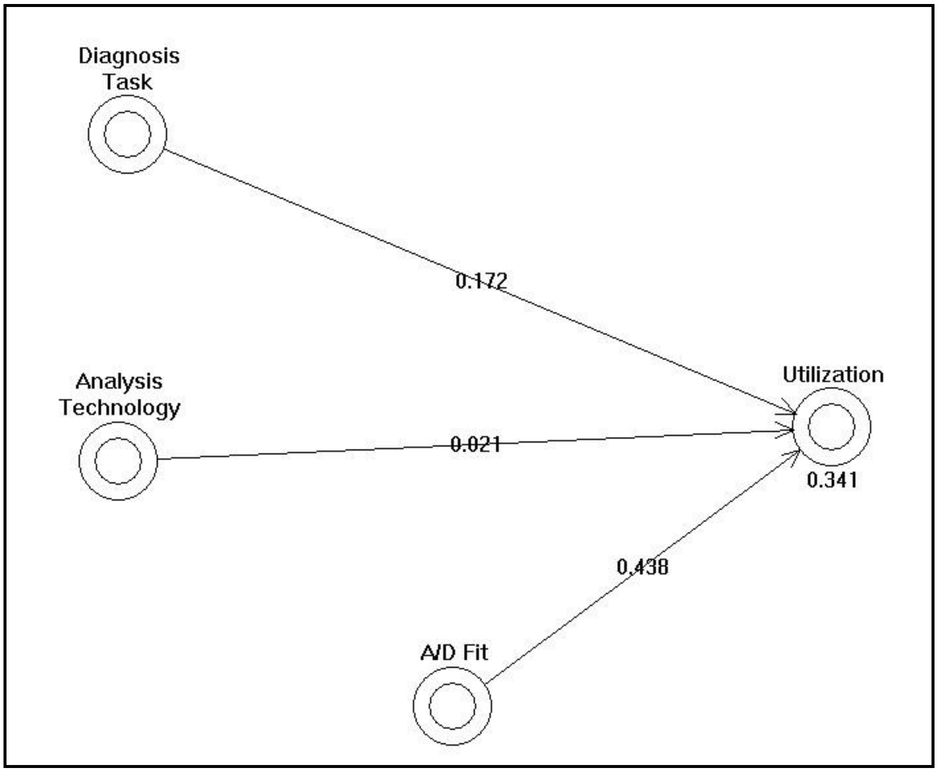

Figure 5. Single Dimension TTF Model, Diagnosis Task and Analysis Technology (Model 1a)

	Paths to Utilization from:		
Path Coefficients:	Analysis	Diagnosis	A/D Fit
Original Sample Estimate	0.0210	0.1720	0.4380
Standard Error	0.0977	0.1375	0.1415
T-Statistic	0.2149	1.2505	3.0949
Sig T (2-tailed)	0.830	0.213	0.002

Table 1. Single Dimension TTF Model, Diagnosis Task and Analysis Technology (Model 1a)

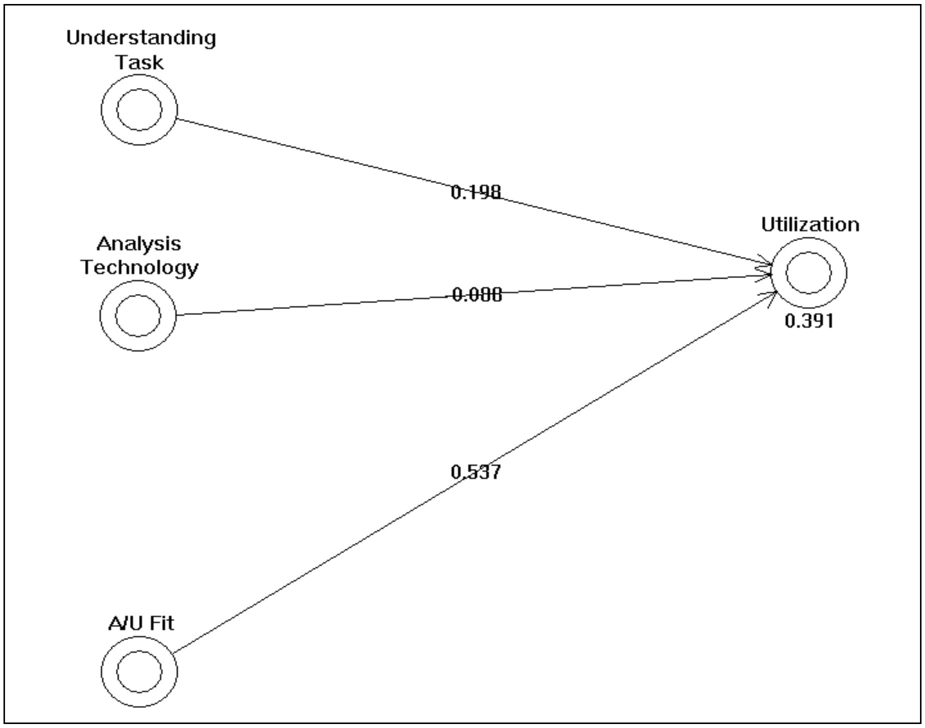

Figure 6. Single Dimension TTF Model, Understanding Task and Analysis Technology (Model 1b)

	Paths to Utilization from:		
Path Coefficients:	Analysis	Understanding	A/U Fit
Original Sample Estimate	-0.0880	0.1980	0.5370
Standard Error	0.0948	0.1322	0.1508
T-Statistic	0.9282	1.4981	3.5607
Sig T (2-tailed)	0.3544	0.1357	0.0005

Table 2. Single Dimension TTF Model, Understanding Task and Analysis Technology (Model 1b)

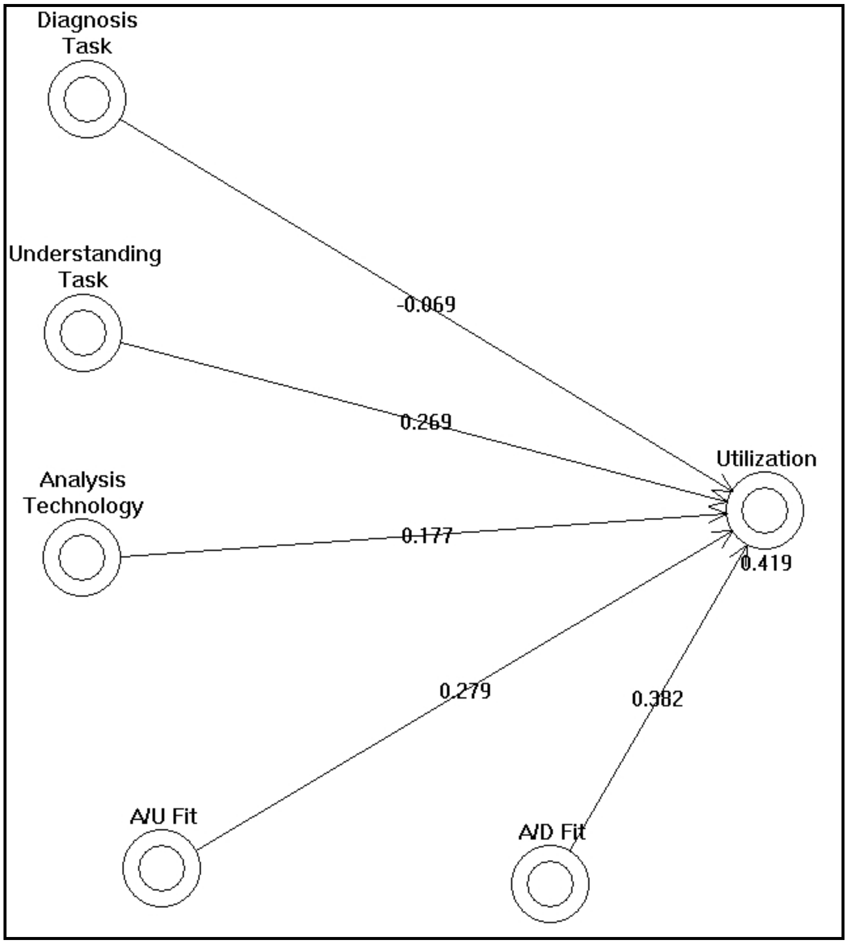

Figure 7. Multi-dimensional TTF Model (Model 2)

	Paths to Utilization from:				
Path Coefficients	Analysis	Diagnosis	Understanding	A/D Fit	A/U Fit
Original Sample Estimate	-0.1770	-0.0690	0.2690	0.3820	0.2790
Standard Error	0.1168	0.1370	0.1501	0.1728	0.1804
T-Statistic	1.5148	0.5036	1.7927	2.2104	1.5468
Sig T (2-tailed)	0.131	0.615	0.075	0.028	0.123

Table 3: Multi-dimensional TTF Model (Model 2)

Model	R^2	R^2 Change	F Change	df1	df2	Sig. F Change
1a	.34	.34	36.804	3	216	.000
2	.42	.08	14.929	2	214	.000

Model 1a Predictors: (Constant), DIAGN, ANALY, ADFIT

Model 2 Predictors: (Constant), DIAGN, ANALY, ADFIT, UNDER, AUFIT

Table 4. Summary of Model 1a vs. Model 2

Model	R^2	R^2 Change	F Change	df1	df2	Sig. F Change
1b	.39	.39	45.739	3	216	.000
2	.42	.03	5.676	2	214	.004

Model 1b Predictors: (Constant), AUFIT, UNDER, ANALY

Model 2 Predictors: (Constant), AUFIT, UNDER, ANALY, DIAGN, ADFIT

Table 5. Summary of Model 1b vs. Model 2

CONCLUSIONS

This study and its results provide additional evidence for an approach to TTF models of assessing task-technology fit using a method of measuring task needs, technology functionality, and deriving fit, an unobserved variable, from these measures. This provides a method for assessing task-technology fit the follows the recommendations of Venkatraman (1989) for assessing the fit as moderation approach. The results indicate that a multi-dimensional version of this approach to a TTF model is feasible, and is at least as good as the single dimension model in explaining software utilization (the outcome variable).

There are limitations to this initial investigation of the feasibility of our proposed approach to assessing multi-dimensional fit. For example, we did not include any variables capturing individual differences, e.g., expertise of the subjects in both the task and the technology, which have been included in some previous studies using TTF models. Because the study reported in this paper was designed to test the feasibility of our proposed approach, there is still much to investigate. We need to investigate the distinctiveness and overlap in our independent variables, test a more complete model, e.g., all the dimensions in Figure 4, and test the model with additional variables, especially those capturing individual differences. Overall, our results suggest that examining additional dimensions could be a productive avenue for future research.

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APPENDIX

Sample Task Items:

- I made extensive use of my knowledge of the software with which the model was created.
- I examined system outputs to obtain clues as to the functioning of the model.
- I had to weigh and evaluate a large volume of information about the system I was modeling.

Sample Technology Items:

- I checked for consistency between different system representations or "models".
- I tested for equivalence of models of processes or modules.
- I searched the system or part of the system for inconsistencies or redundancies in data definitions or data or process models.