Faculty of Economics, Business Administration and Econometrics

Serie Research Memoranda

Task Difficulty, Task Variability and Satisfaction with Management Support Systems: Consequences and Solutions

Research Memorandum 1997-53

Maarten Celderman

October 1997

vrije Universiteit amsterdam

Task Difficulty, Task Variability and Satisfaction with Management Support Systems: Consequences and Solutions

*Maarten Gelderman**
Vrije University Amsterdam
geldermanm@acm.org

September 22, 1997

Abstract

From its inception on, the notion of management support systems (MSS) has been closely linked to task structuredness. Using data collected with a survey questionnaire, this article presents the results of an empirical analysis of the relation between task structuredness and satisfaction with MSS. Two dimensions of task structuredness are distinguished: task difficulty and task variability. The results of the analysis indicate that task difficulty negatively affects satisfaction with MSS, whereas the influence of task variability on MSS success is insignificant. The provision of non-interpreted data generally contributes to satisfaction with MSS. This contribution is larger when task difficulty is high; consequently provision of non-interpreted data fully compensates for the negative effect of task difficulty. However, task variability may frustrate this positive influence. Furthermore, the results of this study indicate that neither daily provision of information, nor the incorporation of DSS-characteristics into MSS, nor interactions of those variables with task difficulty and task variability significantly relate to satisfaction with MSS.

1 Introduction

Task structuredness possibly is the most intriguing variable in management support systems (MSS) research. On the one hand, task structuredness has been used to define the task that MSS ought to support [37, 82], on the other hand, task structuredness has been used to explain success of MSS [36, 61, 63, 75]. This paper takes the latter approach and uses a refined concept of task structuredness to explain MSS success. A major enhancement over previous research, is that this paper investigates the influence of design and environmental characteristics *simultaneously*. In this way,

*This paper is based on my PhD-thesis. I would like to thank my supervisors Cees van Halem and Edu Spoor (both Vrije University Amsterdam) and the members of my reading committee: Gary Bamossy (Vrije University Amsterdam), Tom Groot (Vrije University Amsterdam), David Otley (Lancaster University) and Berend Wierenga (Erasmus University Rotterdam). Furthermore, I wish to express my gratitude for comments on earlier versions of this paper by Wim van der Steede (University of Southern California), Ypke Hiemstra (Vrije University Amsterdam) and participants of the Vrije University Accounting Seminar. Comments are welcome. Before quoting this paper, please contact the author to obtain a more recent version.

not only problems are signaled, but the viability of possible solutions is assessed, as well. The vital constructs in this study are all assessed by rigorously validated measurement instruments. Furthermore, the application of LISREL-modelling allows the incorporation of measurement error into the analyses, thus increasing the accuracy of the results obtained.

In the remainder of this section, the concepts MSS, MSS success, and task structuredness are discussed and the hypotheses are derived from theoretical considerations and findings of earlier research. Section 2 describes the way data to test the hypotheses have been gathered. Results are discussed in Section 3. A summary and a discussion of the findings end the paper.

1.1 Management support systems

Management support systems (MSS) are computerized systems which support managers in the day-to-day tasks in their area of responsibility. This support may be provided both by providing information and by decision aids. Consequently, in this paper traditional decision support systems (DSS), as well as traditional management and executive information systems (MIS and EIS) are treated as manifestations of the more general concept MSS *if* they are used to provide management support. This paper uses the term MSS as a container for all kinds of systems that are used to support managers either directly or indirectly. The term MSS has been choosen because it has less historical connotations than the terms EIS, DSS, MIS etc. This definition of MSS is at least a partial answer to the call of Snitkin and King [78] to revise the definition of DSS based on an 'in use' concept, as the original definition has become overworked.' All systems are included in the analyses, but when appropriate they will be grouped according to the question whether they possess, e.g., certain DSS-chacarteristics (see Section 1.4).

A couple of general characteristics of MSS can be mentioned. MSS support unstructured or semi-structured tasks [6, 41, 70, 71, 75, 78, 87], as the nature of managerial tasks, which they are intented to support, is inherently not structured [64, 65] (the importance of task structuredness will be further discussed in Section 1.3). Consequently, MSS only support managers, but do not replace them; their primary goal is to increase performance of the organization by improving managerial effectiveness rather than managerial efficiency [2,12,24,70,71,77,82].[2] This latter observation is of importance for the operationalization of MSS success (to be discussed in the next section) which will focus on improving decision performance.

1.2 MSS success

The final aim of MSS is to enhance goal attainment of the organization [19, 22, 45, 48, 73] by improving decision performance [5, 16, 76]. Although goal attainment has been employed as a success measure in laboratory studies [11, 60, 84, 88], it is difficult, if not impossible to assess the contribution

'To mention a couple of examples, DSS has be labelled both a subset [14, 37, 66] and a superset [12] of MIS; EIS has been called a layer above MIS [63]; and the distinction between EIS, DSS, MIS etc. has been called diffuse [63, 80].

[2] A similar conclusion is reached by MacIntosh who observes that a MSS is not complete without a manager [56]. Another noteworthy observation is that the aim of improving effectiveness rather than efficiency is a preliminary for the application of UIS.

of MSS to goal attainment in real world situations [22,30,43,45,48,73]. Consequently, in empirical studies MSS success has mainly been operationalized by usage and user information satisfaction (UIS). Gelderman reports in his meta-analysis of factors affecting MSS success that of the 39 studies investigated 17 employed usage as a success criterion, 27 a more or less formal UIS measure and 13 some other measure [31].[3]

The rationale behind the application of usage as a success measure is that a system will only be used if users think the benefits of using it will outweigh the costs [58, 74]. In this way usage is applied as an indirect measure of the users' judgment of the value of the system.[4] This, however, requires usage to be voluntary [8–10, 18, 22, 28, 33, 44, 45, 54, 68]; an assumption that will not be met when usage is officially enforced by organizational guidelines or practically enforced by the culture of the organization or if data are only available through the MSS. Furthermore, the usage measure suffers from the problem that users will only use the MSS when they perceive it to be useful for achieving their own goals. Both the assumption of perfect knowledge and the assumption of goal congruence between user and organization are not necessarily tenable. More problematic, however, is the observation that more usage does not always imply a greater contribution of the MSS to organizational performance, which makes the amount-of-usage criterion unusable as a success measure.[5] Furthermore, the application of a dichotomous usage measure as the success criterion lacks sufficient sensitivity; it will only indentify systems that are not used at all and not differentiate between systems that are used [9].

Whereas usage *indirectly* assesses the users' judgment of the success of the system, UIS *directly* assesses 'the extent to which users believe the information system available to them meets their information requirements' [45, p. 785]. Although UIS also suffers from the shortcoming that it is based on the match between information requirements and information provided as perceived by the user and also may be affected by a lack of goal congruence between user and organization, it does not share the other shortcomings of the usage criterion. Consequently, UIS is the most widely applied success measure in empirical studies on MSS success [20, 31, 42, 62, 79]. In this study, UIS—operationalized by the Doll and Torkzadeh (21,221 instrument—will also be used as the dependent variable. Contrary to the older and more widely used Bailey and Pearson [7] instrument this instrument measures satisfaction with an individual application and not with information in general [42, 43]. An additional reason to prefer the Doll and Torkzadeh instrument above the Bailey and Pearson instrument is that the latter instrument has been criticized for the lack of desirable psychometric properties (discriminant validity, face validity, test/retest relibility), for not including ease-of-use and for the inclusion of items that are not necessarily applicable to each MSS implementation [22, 32, 61, 81].

[3] The sum of the numbers does not equal 39 as some studies employed more than one success criterion.

[4] A more naive rationale is the assumption that the system is always good, but that usage is required for the organization to benefit. In particular, older OR/MS publications tend to neglect the question whether the system itself is valid. Ginzberg, e.g., speaks of 'a gap between our ability to develop new managerial technology and our ability to get managers to use it' [35, p. 459].

[5] Usage may, e.g., increase when performance of the system degrades or if information that is usually requested in concert is distributed over multiple reports.

task variability :	the number of exceptions encountered in the characteristics of the work
task difficulty :	the analyzability and ***predictability*** of the work undertaken by an organization unit [...] both analyzability and predictability indicate the extent to which search processes are trivial and programmed at one extreme or, at the other extreme of the task difficulty continuum, the extent to which they rely upon chance and guesswork

Table 1: Definitions of the two subdimension of task structuredness. Source: [85, Appendix A] with slight adaptations.

1.3 Task structuredness

As has been mentioned above, MSS aim at the support of unstructured tasks. However, the extent to which the tasks supported are unstructured may vary. It is not unlikely that the amount of task structuredness, possibly in interaction with features of the MSS (see Section 1.4) will show a relation with MSS success. Two issues are important with regard to this relation: the direction of the relation and the definition of task structuredness.

From a theoretical viewpoint it can be, and has been, argued that MSS are more successful in less structured task environments, as in those environments the need for support will be higher [36, 63, 75]. Indeed, cases have been described where environmental turbulence is an important reason for MSS adoption [26]. McKeen, Guimaraes and Wetherbe [61] found a positive, but insignificant, relation between UIS and task complexity and found task complexity to be a significant moderator of the influence of user involvement on UIS. Among their sample of managers, Sanders and Courtney [75] found a positive, but not significant, relation between task difficulty and task variability and UIS, and a positive, significant effect for task newness.

From a more practical viewpoint, it has been claimed that MSS development is more difficult for less structured tasks and consequently the changes of MSS will decrease when tasks are less structured [25, 27, 34, 55–57, 59, 64]. It has also been claimed that MSS success will reach an optimum for semi-structured tasks [75], which also implies a negative relation between MSS success, as structured tasks are unlikely to be supported by MSS. Furthermore, it has been remarked that MSS brought some decisions from the unstructured to the structured area [5, 77]. This may imply that MSS development induced managerial or organizational learning, a generally acknowledged benefit of MSS development [58, 82]. However, it may also represent a mismatch between MSS and the organizational environment, which will negatively affect MSS success.

Overall, the argument that MSS will be less successful for unstructured tasks is most convincing: the claims that MSS will be more successful mainly focus on the need for support, whereas the arguments claiming less MSS success focus on the question whether it is really possible to provide this support. A preliminary hypothesis is that task structuredness has a negative influence on UIS (which in this study is the proxy for MSS success). Before this hypothesis can be made more specific, the definition of task structuredness deserves additional attention.

The task of integrating the diverse notions of task structuredness available from the literature has been undertaken by Van de Ven and Ferry [85]

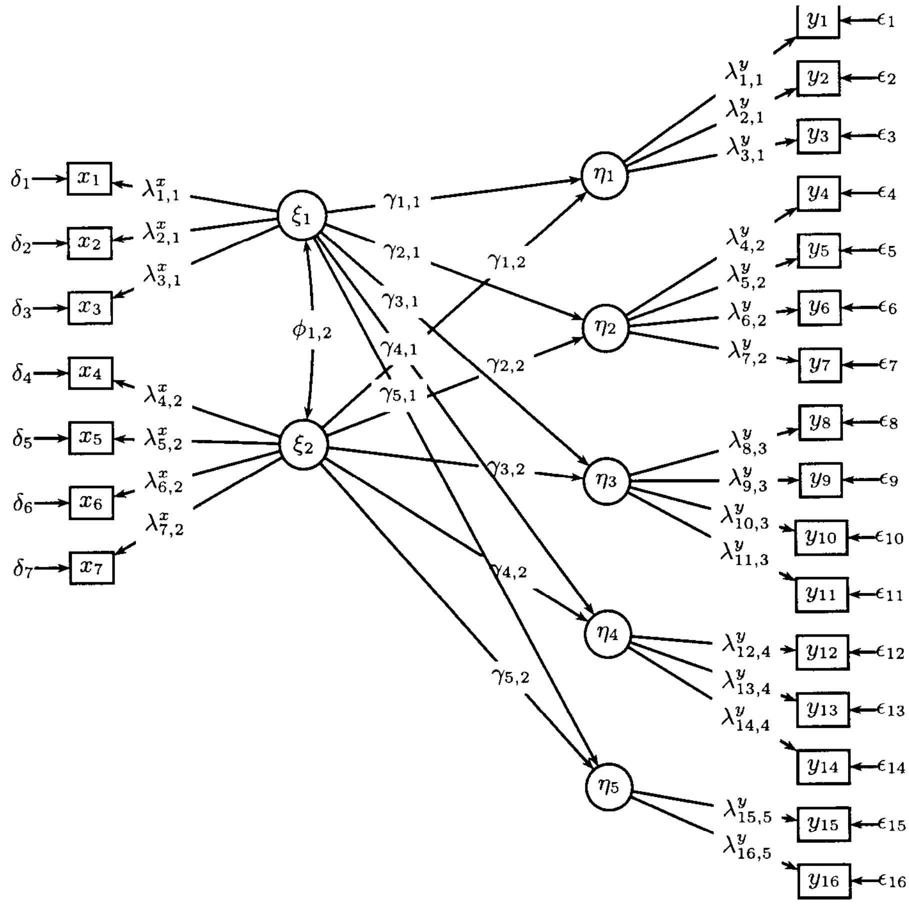

Figure 1: Path model for hypothesis la and lb, representing the influence of task variability (ξ_1) and task difficulty (ξ_2) on the five components of UIS: content, accuracy, format and timeliness of information provided by the MSS (η_1 to η_4) and the ease-of-use of the MSS (η_5). In order to enhance readability ζ's and ψ's are omitted. However, Ψ is supposed to be a free symmetrical matrix.

in their seminal work on organizational assessment. In an elaborate study, which theoretical foundations include the work of Simon, March and Galbraith, they distinguish between two dimensions of task structuredness: task difficulty and task variability (see Table 1). Their definitions and measurement instruments have been adopted in this study. The preliminary hypothesis mentioned above can now be formulated as:

Hypothesis la *Task* variability *has a* negative *influence* on UIS.

Hypothesis lb *Task difficulty* **has** *a negative influence on* UIS.

The path model used to test both hypotheses simultaneously is represented in Figure 1.[6]

[6]See Appendix A for a short introduction to the notation used in this figure and the remainder of this paper. All analyses in this paper have carried out using the Windows version of **LISREL** 8. The results presented are based on analysis of the Spearman rank order correlation matrix calculated by PRELIS and presented in Appendix C. Results of analysis on an ordinary correlation matrix in which all variables were treated as ordinal according to the procedure prescribed by Jöreskog and Sorbom [47] lead to

1.4 Interactions between MSS characteristics and task structuredness

The DSS-characteristics—what-if analysis and simulation, trends and prediction, and planning functionality-in an MSS are meant to support prediction and analysis. However, if task difficulty is high, predictability and analyzability of the task at hand are low by definition [85] and consequently DSS characteristics cannot be embedded in the MSS; if they are, they will generally be flawed and hence users will not be satisfied with the support provided by the system [34]. The following hypothesis is derived from this statement:

Hypothesis 2 *If the* MSS *provides typical* DSS-*characteristics and task difficulty* is *high, users are* less satisfied *with their* MSS.

On the other hand, it has been claimed that the problems allegedly associated with task difficulty may be overcome by the provision of 'non-interpreted data'-data that not have been reduced to a bottom-line number (operationalized[7] by non-financial quantitative data, qualitative data, external data, and drill-down functionality) [27,36,55–57]. Similarly, in situations of high task variability, the reduction of non-interpreted data to bottom line numbers may not be effective, as the number of exceptions encountered may be too large to make this bottom-line number meaningful. Hence, if task variability is high, the provision of non-interpreted data is also a possible solution. Although the provision of non-interpreted data is most desirable in situations of high task difficulty and variability, it has also been argued that this feature in general is advisable [6,65]. The following hypotheses are derived from those statements:

Hypothesis 3 *The provision of* non-interpreted *data positively affects* UIS.

Hypothesis 4a *The positive effect of the provision of non-interpreted data* on UIS *is larger if task variability is high.*

Hypothesis 4b *The positive effect of the provision of non-interpreted data* on UIS is larger *if task difficulty is high.*

2 Research method

A questionnaire survey among Dutch managers was used to collect the evidence needed to test the hypotheses discussed in the previous section. Response rates are presented in Table 2 and are comparable to response rates usually obtained in MIS studies (see Appendix B). A somewhat complicated design was needed to collect sufficient data to ensure the convergence of the measurement model of the structural equation model described in the previous section. Two lists of managers were obtained: a list consisting of a sample of Dutch CEOs and CFOs and a list containing a sample of managers, information managers and controllers.[8] As the Van de Ven and Ferry measures are rather elaborate, inclusion of those measures in the questionnaire administered to CEOS and CFOs, was deemed undesirable because of

similar results.

[7]The way in which the provision of non-interpreted data will be operationalized in the analyses implies that only the presence of non-interpreted data is included in the definition. The absence of interpreted data is not required.

[8]Subjects appearing in both lists were eliminated from the second list before the questionnaire was administered.

	large		small		total	
	#	%	#	%	#	%
sample	474	100"	550	100"	1024	100"
refusals	20	4.2	22	4.0	42	4.1
useful response	83	17.5	87	15.8	170	16.6
gross response	103	21.7	109	19.8	212	20.7
non-resoonse	371	78.3	441	80.2	812	79.3

"Due to rounding errors the sum of the individual items does not always equal 100%

Table 2: Response rate by type of questionnaire.

the risk of a dramatically low response rate.[9] Consequently, the CEO/CFO data were not of direct usage for the research questions of this study. However, they were used to validate and estimate the measurement model of the UIS measures. A 12-page questionnaire" was administered among the managers appearing on the second list. An MSS was not available to all respondents. However, respondents without an MSS also answered the Van de Ven and Ferry questions and all answers were used to validate and estimate the measurement model for task difficulty and task variability.

2.1 Descriptive statistics

The age of the respondents varies from 23 to 65 years, with an average of 44.9 years. On average respondents have worked 6.1 years in their current function and 11.2 years with their current employer. A large majority of the respondents (94.7%) is male. Of the respondents 84% has at least a polytechnic, university, CPA or CMA degree." An MSS is available to 64.5% of respondents. However, 11.4% do never use this system. A breakdown by category of usage of MSS is provided in Table 3. An overview of the functionality available in the systems used by the respondents is provided in Table 4. Almost every system provides financial data. A large majority also provide quantitative non-financial data. Graphics are available to 57% of the respondents. Slightly less than 50% indicates that the system provides information on performance indicators. The least present elements in the MSS available are external data, what-if analysis and simulation, and qualitative data. Trends and prediction, planning functionality and drill-down functionality are present in about one third of the systems surveyed.

2.2 Reliability and validity of measurement instruments

Traditional reliability analysis (Cronbach's α), confirmatory factor analysis (CFA) and an expert panel were used to assess reliability and validity of the measurement instruments. Following a procedure suggested by the American Psychology Association [3] an expert panel, consisting of three members of faculty and two management consultants, was provided with a list of 34 variables and a **copy** of the questionnaire from which headings explicitly

[9] The questionnaire administered to those managers was mainly used to gather data for another **MSS** related project of our department and had a total length of 6 pages.

[10] Besides the data needed for this study this questionnaire did also contain questions relevant to another research project of our department.

[11] The subjects were Dutch managers, the original questions concerned **HBO,** wo, **RA** and **RC,** respectively.

	management top	middle[a]	staff	other	total
use system themselves	23.3	12.0	28.3	50.0	23.8
use system through intermediary	43.3	12.0	23.9	25.0	26.7
use system both themselves and through intermediary	23.3	60.0	37.0	25.0	38.1
do not use system	10.0	16.0	10.9	0.0	11.4
total	28.6	23.8	43.8	3.8	100.0[b]

[a] Aggregration of division, business unit and line management.
[b] Due to rounding errors the sum of the individual items does not always equal 100%

Table 3: Breakdown of MSS usage by category (n = 105).

functionality	%
financial data	88.8
quantitative non-financial data	77.6
qualitative data	23.4
performance indicators	48.6
external data	14.0
drill-down	32.7
what-if/simulation	22.4
trends and prediction	30.8
planning functionality	37.4
graphics	57.0

industry	%
manufacturing[a]	41.9
government and non-profit	14.4
financial services	11.9
wholesale	6.3
transportation	5.0
communication	5.0
energy	5.0
building	5.0
other	5.7
total[b]	100.0

[a] Including food industry.
[b] Due to rounding errors the sum of the individual items does not always equal 100%.

Table 4: Descriptive statistics.

indicating the nature of the variables measured were removed. The experts were informed that each question was supposed to measure one variable and that each variable could be measured by multiple questions and were asked to indicate for each question which variable it would measure. The face validity of a scale is defined as:

$$\text{face validity} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{n_i}\sum_{j=1}^{n_i} y_{ij}\right)\cdot 100\% \qquad (1)$$

Where m is the number of items in the scale, n_i is the number of experts that classified item i, and

$$y_{ij} = \begin{cases} 0 & \text{if the expert did not mention the intended variable} \\ \frac{1}{q} & \text{if the expert mentioned } q \text{ variables, including the intended one} \\ 1 & \text{if the expert only mentioned the intended variable} \end{cases}$$

Task difficulty and task variability each were measured by four questions from the Van de Ven and Ferry instrument. The fourth item of the task variability scale showed low face validity (10%) and CFA showed an item reliability of 0.12. This item was eliminated from further analyses, which resulted in an increase in α from 0.66 to 0.71. Further results of the CFA indicate that the assumption of parallel measures-implicitly assumed by

scale	n	# items	α	mean	s.d.	F.V.
task difficulty	85	4	0.64	10.91	2.9	70%
task variability	83	3	0.71	10.93	1.8	67%
UIS	102	19	0.97	67.8	15.9	n/a
content	102	3	0.90	10.3	2.9	88%
accuracy	102	4	0.97	16.1	3.8	100%
format	102	4	0.94	13.2	4.1	90%
timeliness	102	3	0.91	11.2	2.9	93%
ease-of-use	102	2	0.96	6.4	2.2	100%

Table 5: Reliabilities (Cronbach's α) mean, standard deviation and face validity (as defined in Equation 1) for summed scales.

Van de Ven and Ferry-is tenable (assuming congeneric, r-equivalent, and parallel measures[12] results in χ^2_{13} = 12.85, χ^2_{18} = 13.91, and χ^2_{23} = 14.11, respectively), confirm discriminant validity (χ^2_1 = 16.21), and indicate that the null-hypothesis of equivalence between observed and implied covariance matrix cannot be rejected (p = 0.92) and an oblique factor model is preferred over an orthogonal model (χ^2_1 = 3.72): the measurement model fits the data reasonably well, and the significant result for discriminant validity indicates that variability and difficulty, although correlated, are statistically clearly distinct. Furthermore, as indicated in Table 5, both scales show moderate but acceptable αs.[13]

To assess UIS the Doll and Torkzadeh [22] instrument was used. As the timeliness dimension of this instrument consists of only two items, two new items were added.[14] Both the three accuracy items, the two format items and the ease-of-use item eliminated by Doll and Torkzadeh were included in a preliminary version of the questionnaire. After a pilot study among student subjects one of the content items was again eliminated, but the other items were retained in the final version of the questionnaire. One of the remaining content items was assigned to the correct latent variable by only one expert. This items was eliminated from further analyses. The CFA indicated problems with the third ease-of-use item, which was also eliminated. Furthermore the first new timeliness-item was classified correctly by only 40% of the judges and was also eliminated. As indicated in Table 5 the αs of the resulting scales are high. The results of the CFA indicate that the UIS scales are r-equivalent (goodness-of-fit for congeneric, r-equivalent, and parallel measures are χ^2_{94} = 149.64, χ^2_{105} = 156.45, and χ^2_{116} = 181.30, respectively). Although the α's for the UIS measures are better than those of the task difficulty and variability measures, the null-hypothesis of equal

[12] Congeneric measurement is assumed in the traditional factor model, r-equivalent measures are nested in congeneric measures as all factor loadings (X) are supposed to be equal and parallel measurement is in turn nested in -r-equivalent measurement as error variances of the individual items (6) are also supposed to be equal [47], in the latter case the score for the scale can be obtained by summing up the scores of the individual items without a loss of information.

[13] In all subsequent analyses the measurement model and the covariance matrix of the task structuredness variables have been fixed to ensure identification.

[14] By using at least three indicators for each latent variable identification of a congeneric measurement model is ensured [13]. Furthermore, the timeliness scale showed some instability accros the 1988 [22] and the 1994 [23] Doll et al. studies of the properties of this instrument. The two new questions are 'Are the data in the system updated often enough?' and 'Are the data in the system updated *quickly* enough?'

parameter	model A value	t	model B value	t	model value	t
$\gamma_{1,1}$	0.22	1.09	0	n/a	0.07	0.40
$\gamma_{2,1}$	0.04	0.19	0	n/a	-0.02	-0.13
$\gamma_{3,1}$	0.04	0.21	0	n/a	-0.12	-0.69
$\gamma_{4,1}$	0.12	0.61	0	n/a	-0.12	-0.66
$\gamma_{5,1}$	0.00	-0.01	0	n/a	-0.17	-1.01
$\gamma_{1,2}$	-0.30	-1.45	-0.19	-1.03	0	n/a
$\gamma_{2,2}$	-0.12	-0.59	-0.10	-0.57	0	n/a
$\gamma_{3,2}$	-0.33	-1.61	-0.31	−1.75	0	n/a
$\gamma_{4,2}$	-0.48	-2.40	-0.42	-2.42	0	n/a
$\gamma_{5,2}$	-0.37	-1.84	-0.37	-2.13	0	n/a
χ^2	202.09		204.69		213.27	
d.f.	233		238		238	
GFI	.77		.77		.76	
AGFI	.73		.73		.72	
standardized RMSR	.07		.07		.09	

Table 6: Standardized estimates of the influence of task variability and task difficulty on UIS. Sample-size dependent statistics are based on 49 observations. See Appendix C for further details.

implied and observed covariance matrices should be rejected in this case-a common observation of CFA, which in this case indicates that the development of a better UIS instrument is still worthwhile. The viability of using a r-equivalent measurement model eliminates some potential problems with identification of the ease-of-use scale. Not unexpectedly, an oblique measurement model is prefered over an orthogonal model (χ^2_{10} = 450.84). Discriminant validity of the UIS measures is also confirmed by the CFA (all χ^2_1-statistics are larger than 90): the UIS measures are correlated, but each subdimension is distinct from the other subdimensions.

3 Results

First the structural equation model presented in Figure 1 was estimated to test hypotheses la and lb. The aim is to assess the significance of the simul*taneous* effect of task variability (task difficulty) on the five UIS measures. A hierarchical approach is appropriate in this case. If task variability (task difficulty) affects UIS, and the model specification implies that this effect ($\gamma_{1-5,1}$ and $\gamma_{1-5,2}$, respectively) equals zero, model fit will decrease compared to the model in which $\gamma_{1-5,1}$ ($\gamma_{1-5,2}$) is left free. The significance of this decrease is assessed by a χ^2-test: the difference in χ^2 between the model in which the influence is fixed at zero and in which the influence is left free, has a χ^2-distribution with degrees of freedom equal to the the number of estimated parameters that has been fixed at a given value (0 in this case).[15]

The results of this analysis are presented in Table 6. Model A is the path model presented in Figure 1. In model B the influence of task variability is fixed at zero, and in model c the influence of task difficulty is fixed

[15]The number of degrees of freedom in those analyses is not based on the number of respondents, but on the number of elements of the covariance matrix and equals $\frac{n(n+1)}{2} - k$, where n is the number of manifest variables and k is the number of parameters to be estimated.

at zero. The χ^2-statistics indicate that elimination of the effect of task variability on UIS does not result in a significant decrease in fit of the model—hypothesis la cannot be confirmed. Model c is obtained by elimination of the influence of task difficulty on UIS. This results in a significant ($\chi^2_5 = 11.18$; $\alpha < 0.05$) decrease in model fit. Consequently, model B (in which only task difficulty influences UIS) is the preferred model. An investigation of the individual parameter estimates confirms hypothesis lb: task difficulty negatively affects UIS.

To test hypothesis 2 through 4 MANOVA was used.[16] Where necessary, respondents were assigned to either a high or low task variability (difficulty) group by ranking them on their unweighted (the measures are T-equivalent) task variability (difficulty) scores. A high and low DSS-characteristics group were created by ranking respondents on the number of typical DSS-features—what-if analysis and simulation, trends and prediction, and planning functionality-present in their MSS. Membership of the high and low non-interpreted data group was determined by ranking respondents on the number of non-interpreted data elements-quantitative non-financial data, qualitative data, external data, and drill-down functionality-provided by their MSS. After ranking respondents on a system or task characteristic, the upper 50% were assigned to the 'high' and the lower 50% to the 'low' task or system characteristic group. In all analyses the task variability and difficulty score were used as a covariate, if not otherwise present in the analysis. The average scores on each of the five UIS measures were used as the dependent variables.

	$F_{5,40}$	p	power"
Task variability (covariate)	0.497	0.777	0.27
Task difficulty * Dss-characteristics	1.401	0.245	0.58
Dss-characteristics	0.337	0.888	0.21
Task difficulty	2.623	0.038	0.84

"Exact power at $\alpha < 0.10$

Table 7: MANOVA for hypothesis 2.

Hypothesis 2 predicts that when task difficulty is high, the provision of DSS-functionality in an MSS will imply lower satisfaction with ease-of-use of the MSS and content and accuracy of the information provided. Examination of the cell means (not presented) shows that this hypothesis should be rejected for the simple reason that in the high task difficulty group all five UIS scales yield a higher score for the high DSS group. However, the results in Table 7 show that neither this opposite effect nor the main effect of the introduction of DSS-functionality is significant.[17]

[16] MANOVA is a technique equivalent to ANOVA, but suited to assess the influence of a factor on multiple dependent variables-the five subdimensions of UIS—without sacrificing the accuracy of the significance level reported. Ail relations have been assessed using ANOVA, as well. The results of the ANOVAS are presented as footnotes to the results of the MANOVA.

[17] MANOVA requires equal variances in all cells. Neither the F nor the χ^2 approximation of Box's M indicates problems with equality of variance. Results of an ANOVA, where the average of the five scales has been used as the dependent variable, are comparable to the results presented in Table 7: with the exception of task difficulty none of the influences is significant.

	$F_{5,40}$	p	power[a]
Task difficulty (covariate)	3.716	0.007	0.95
Task variability * non-interpreted data	3.094	0.019	0.90
Non-interpreted data	4.659	0.002	0.98
Task variability	1.028	0.415	0.46

[a]Exact power at $\alpha < 0.10$

	$F_{5,40}$	p	power[a]
Task variability (covariate)	0.314	0.902	0.20
Task difficulty * non-interpreted data	2.182	0.075	0.77
Non-interpreted data	3.319	0.013	0.92
Task difficulty	3.279	0.014	0.92

[a]Exact power at $\alpha < 0.10$

Table 8: MANOVA for hypotheses 4a and 4b.

Hypotheses 4a and 4b were also tested using MANOVA. The results in Table 8 show that the interaction between task variability and the provision of non-interpreted data is significant. However, examination of the means (not presented) indicates that hypothesis 4a cannot be confirmed. The provision of non-interpreted data generally contributes to UIS, the results in Table 8 indicate that this contribution is significant. In the high task variability group, however, the provision of non-interpreted data contributes significantly less to the increase in UIS than in the low task variability group. Investigation of the univariate results shows that this is in particular caused by the satisfaction with content and timeliness of information.[18]

The results presented in Table 8 indicate that provision of non-interpreted data is more valuable in the high task difficulty situation than in the low task difficulty group ($\alpha < 0.10$). Examination of the means reveals that the interaction effect of task difficulty and non-interpreted data and the main effect of non-interpreted data compensate for the negative effect of task difficulty. That is, users in the high task difficulty group with non-interpreted data are on average about as satisfied with their system as users in the low task difficulty group without those data.[19]

[18]MANOVA requires equal variances in all cells. The null-hypothesis of equality of cell variances cannot be rejected, so the results are apparently valid in this respect. The analysis was repeated using ANOVA with the average of the UIS scales as the dependent variable. The results were similar to the results of the MANOVA, but this time the interaction was not significant ($F_{1,44} = 1.42$), which confirms the impression that the content and timeliness scales are mainly responsible for the finding.

[19]For this MANOVA the requirement of homogeneity of variances can be maintained. An ANOVA on the average of the five scales has also been carried out. Tests for homogeneity of variance where inconsistent in this case: Cochran's C does not reject the null hypothesis of equal variances across cells ($p \approx 0.32$), but the Bartlett-Box test does (p = 0.086). Results of the ANOVA are similar to results of the MANOVA. $F_{1,44}$-values for interaction, task difficulty and non-interpreted data are respectively 4.61, 9.14 and 7.09. All three values are significant at $\alpha < 0.05$.

4 Summary and discussion

4.1 Findings and implications

The LISREL-analyses presented in this paper indicate that of both dimensions underlying task structuredness, task variability and task difficulty, only the latter directly influences satisfaction with MSS. This result is confirmed by the MANOVAs presented in this paper. Mintzberg [64] and Ginzberg [34] are apparently right when they claim that it is not possible to provide adequate support for tasks that the developer of a system does not understand. However, although the predictions based on the considerations mentioned by both authors hold for UIS in general, the individual parameter estimates presented in Table 6 indicate that satisfaction with ease-of-use of the system and format and timeliness of information suffer more strongly than satisfaction with content and accuracy of information, as would be the most appealing conclusion of the statements of both authors.

Concerns regarding the possibly negative influence of incorporating DSS-characteristics in MSS (expressed in hypothesis 2) when task difficulty is high appeared to be superfluous: the presence of DSS-characteristics does not show a relation with UIS. Systems designers do not have to worry about providing such features, although on average they do not seem to contribute to satisfaction either. The results presented in Table 8 confirm hypothesis 3 which predicted that the provision of non-interpreted data would positively affect satisfaction with MSS and hypothesis 4b which indicated that satisfaction would increase more if task difficulty is high. Hypothesis 4a could not be confirmed, however. If task variability is high, the provision of non-interpreted data is less successful. Practitioners may learn that the provision of non-interpreted data-and this concept maps fairly well on the features provided by modern OLAP-tools—in general is beneficial, that this feature gets more beneficial if task difficulty is high, and in the latter case even may fully compensate for the negative effect of task difficulty. However, task variability may negatively affect this positive influence. An explanation for the latter finding may be that ad hoc reporting-which is most needed if task variability is high-is too difficult to use for most managers.[20]

4.2 Discussion and suggestions for further research

A first and major point of concern is the occurence of interactions between the success measure applied in this paper (UIS) and the findings of the analysis. The negative influence of task difficulty on UIS might for instance be explained by the fact that task difficulty implies that managers have an incomplete model of their decision situation. Already in 1967, Ackoff [1] claimed that managers with such an incomplete model want to play it safe and want to obtain as much information as possible. This may imply that they desire more information than can economically be justified. If their MSS only provides as much information as can be justified, the system is satisfactory, but the manager's evaluation of the system will not reflect the contribution of the MSS to organizational performance. Other

“Findings from software evaluation in a usability-laboratory in which the author of this paper has been involved indicate that the ad hoc reporting facilities provided in most OLAP tools are too complicated to be used by managers and controllers without elaborate training.

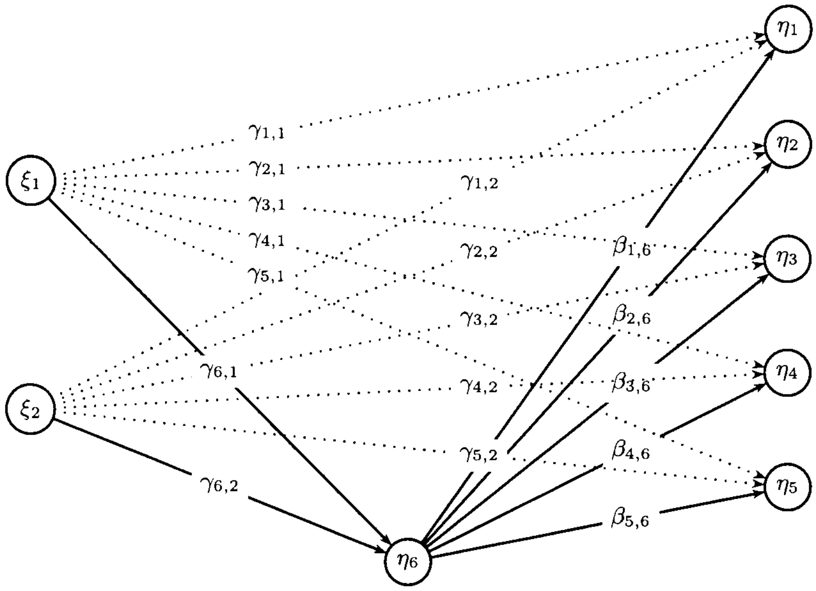

Figure 2: Indirect influence model. In order to enhance clarity the measurement model, ϕ's, ζ's and ψ's have been omitted; ζ's of the structural equations determining UIS variables are allowed to correlate; ξ_1 and ξ_2 depict task variability and task difficulty, respectively; η_1 to η_4 depict content, accuracy, format and timeliness of the information provided; η_5 depicts ease-of-use; η_6 is the degree to which respondents are of the opinion that they receive too little information.

authors have indicated that high task difficulty and task variability indicate that managers need more information [29, 55–57, 69]. Consequently, low UIS scores would be explained by dissatisfaction with the amount of information provided.In order to test this alternative hypothesis, the indirect influence model presented in Figure 2 has been estimated.

If the rival hypothesis is true, one would expect that high task variability and high task difficulty cause the respondents to complain about the availability of too little information. Those complaints in turn would cause low UIS. This would imply that fixing the parameters represented by the dotted lines at zero, would not result in a decrease in model fit. From the analyses presented above, it is already known that the influence of task variability on UIS is insignificant. Consequently, the question is whether fixing $\gamma_{1-5,2}$ at zero results in a decrease in model fit. This decrease in model fit indicates the direct influence of task difficulty on UIS after an indirect effect through dissatisfaction with the amount of information provided has been taken into account. Estimation of a model in which $\gamma_{1-5,2}$ is left free results in χ^2_{254} = 217.38, whereas the estimating of a model in which those parameters are fixed at zero results in χ^2_{259} = 229.25. The difference between both models is significant (α < 0.05): even after correction for dissatisfaction because too little information is provided a significant influence of task difficulty remains.[21]

[21] In this analysis the opinion of respondents that they receive too little information was used as a dependent variable. A second analysis was run in which the opinion of respondents that they receive the wrong amount (either too little or too much) of information was used as the intermediate variable. In this case the significance of the

It also has been indicated that not only the amount of information, but also frequency of reporting causes problems in unstructured situations. Providing information more frequently would be beneficial in such circumstances [36, 55–57, 69]. MANOVA was used to assess whether the daily provision of information-a better operationalization of frequency of reporting was unfortunately not available-would alleviate the problems caused by task structuredness. The results of this analysis are presented in Table 9. The results indicate that neither the interaction between daily reporting and task variability, nor the interaction between daily reporting and task difficulty is significant. However, those findings should be treated with caution. The assumptions of MANOVA are not met in this case. Investigation of univatiate results indicates that daily reporting positively affects satisfaction with format, timeliness and ease-of-use. The interactions with task variability and task difficulty are not significant in this case either.

	$F_{5.40}$	p	power[a]
Task difficulty (covariate)	2.195	0.074	0.77
Task variability * daily reporting	0.462	0.802	0.26
Daily reporting	1.409	0.242	0.58
Task variabilitv	0.585	0.711	0.30

"Exact power at a < 0.10

	$F_{5.40}$	p	power[a]
Task variability (covariate)	0.401	0.845	0.24
Task difficulty * daily reporting	0.337	0.888	0.21
Daily reporting	1.979	0.103	0.73
Task difficulty	2.298	0.063	0.79

"Exact power at $\alpha < 0.10$

Table 9: MANOVA for the influence of daily reporting.

Another possible interaction with UIS is the observation that the contribution to UIS of providing non-interpreted data might be interpreted as a tendency of users to show 'greater comfort with a DSS that encourages a pattern matching strategy that seems natural' [40, p. 62]. Fortunately, the Hoch and Schkade [40] study not only raises, but at the same time refutes concerns evoked by this comment as their laboratory experiment did demonstrate that decision performance increased simultaneously.

An indisputable limitation of this study is introduced by the method—survey research-applied. A zero influence may have been found for variables that in fact have a devastating impact on MSS success. In cases where the system is a total failure, it may, as has been remarked in the discussion of another research project, 'fall rapidly into disuse and [may be] quickly forgotten, the present sample really contains DSS that range from very successful to "somewhat" unsuccessful' [9, p. 266]. Due to the research method used such failed systems will be underrepresented in the sample. Only longitudinal research and intensive case studies may reveal the factors that caused their collapse.

Finally, a point that is worth further investigation is the lack of findings for the accuracy-dimension of UIS. This subdimension of UIS fails to show

remaining influence of task difficulty reduced to a < 0.10

a relation with the task characteristics. If the MANOVAS presented above are repeated using ANOVA on the individual subdimensions, accuracy does not show a significant relation with any of the factors investigated in this paper. [22] One can only speculate about an explanation for this phenomenon. It might be the case that accuracy is not a valid subdimension of UIS because managers either deem accuracy to be not relevant, or are not able to make an assessment of the accuracy of the information provided. This topic certainly deserves attention in future research.

References

[1] Russell L. Ackoff. Management misinformation systems. Management Science, 14(4):B:147–B:156, December 1967.

[2] Maryam Alavi and John C. Henderson. An evolutionary strategy for implementing a decision support system. Management Science, 27(11):1309–1323, November 1981.

[3] American Psychological Association, Washington, DC. Standards *for educational* and *psychological testing,* 1985.

[4] James S.K. Ang, Chee-Chuong Sum, and Wah-Fook Chung. Critical success factors in implementing MRP and government assistance: a Singapore context. Information & Management, 29(2):63–70, 1995.

[5] Robert N. Anthony. *The* management *control* junction. Harvard Business School Press, 1988.

[6] Gad Ariav and Michael J. Ginzberg. Dss design: a systemic view of decision support. Communications *of the ACM,* 28(10):1045–1052, October 1985.

[7] James E. Bailey and Sammy W. Pearson. Development of a tool for measuring and analyzing computer user satisfaction. Management Science, 29(5), May 1983.

[8] H. Barki and S.L. Huff. Implementing decision support systems: correlates of user satisfaction and system usage. INFOR (Canada), 28(2):89–101, May 1990.

[9] Henri Barki and Sid L. Huff. Change, attitude to change, and decision support system success. Information & Management, 9(5):261–268, December 1985.

[10] Jack J. Baroudi, Margrethe H. Olson, and Blake Ives. An empirical study of the impact of user involvement on system usage and information satisfaction. *Communications of* the *ACM,* 29(3):232–238, March 1986.

[11] Izak Benbasat, Albert S. Dexter, and Paul S. Masulis. An experimental study of the human/computer interface. Communications *of the ACM*, 24(11):752–762, 1981.

[12] John L. Bennett, editor. *Building* decision *support systems.* Addison-Wesley series on decision support. Addison-Wesley, 1983.

[13] Kenneth A. Bollen. *Structural* equations *with* latent variables. Wiley series in probability and mathematical statistics. Applied probability and statistics section. John Wiley & Sons, 1989.

[14] Eric D. Carlson. An approach for designing decision support systems. In Bennett [12], chapter 2, pages 15-39.

[15] Patrick Y.K. Chau. Factors used in the selection of packaged software in small businesses: views of owners and managers. Information & Management, 29(2):71-78, 1995.

[16] Paul H. Cheney and Gary W. Dickson. Organizational characteristics and information systems: An exploratory investigation. Academy *of* Management *Journal*, 25(1):170–184, 1982.

[17] Deborah R. Compeau and Christopher A. Higgins. Computer self-efficacy: Development of a measure and initial test. MIS *Quarterly,* pages 189-211, 1995.

[18] Fred D. Davis. Richard P. Bagozzi, and Paul R. Warshaw. User acceptance of computer technology: a comparison of two theoretical models. Management Science, 35(8):982–1003, August 1989.

[22] This also implies that the results presented earlier would be more significant if accuracy had been ommitted from the UIS-measure.

[19] B. DeBrabander and G. Thiers. Successful information system development in relation to situational factors which affect effective communications between MIS-users and EDP-specialists. Management Science, 30(2):137–155, February 1984.

[20] William H. DeLone and Ephraim R. McLean. Information systems success: the quest for the dependent variable. Information Systems Research, 3(1):60–95, 1992.

[21] William J. Doll, T.S. Ragahunathan, Jeen-Su Lim, and Yash P. Gupta. A confirmatory factor analysis of the user information satisfaction instrument. *Information* Systems *Research,* 6(2):177–188, 1995.

[22] William J. Doll and Gholamreza Torkzadeh. The measurement of end-user computing satisfaction. MIS Quarterly, 12:259–274, June 1988.

[23] William J. Doll, Weidong Xia, and Gholamreza Torkzadeh. A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly,* pages 453-461, December 1994.

[24] James S. Dyer and John M. Mulvey. Integrating optimization models with information systems for decision support. In Bennett [12], chapter 5, pages 89–110.

[25] Philip Ein-Dor and Eli Segev. Organizational context and the success of management information systems. *Management* Science, 24(10):1064–1077, June 1978.

[26] Joyce J. Elam and Dorothy G. Leidner. EIS adoption, use, and impact: the executive perspective. *Decision Support Systems,* 14(2):89–103, 1995.

[27] Kweku Ewusi-Mensah. The external organizational environment and its impact on management information systems. *Accounting, Organizations and Society, 6(4):301*-316, 1981.

[28] P.N. Finlay. Measures of success for lone-user management support systems. *Journal* of *Information* Systems, 3:47–67, 1993.

[29] Jay Galbraith. *Designing* complex organizations. Organization Development. Addison-Wesley, 1973.

[30] Amy W. Gatian. Is user satisfaction a valid measure of system effectiveness? *Information* & Management, 26:119–131, 1994.

[31] Maarten Gelderman. Factors affecting the success of management support systems: analysis and meta-analysis. Paper presented at the IS/MAS forum of the Annual Conference of the American Accounting Association, Orlando, Florida, August 1995.

[32] Leopoldo A. Gemoets and MD Adam Mahmood. Effect of the quality of user documentation on user satisfaction with information systems. Information & Management, 18:47–54, 1990.

[33] Michael J. Ginzberg. Finding an adequate measure of OR/MS effectiveness. *Interfaces,* 8(4):59–62, August 1978.

[34] Michael J. Ginzberg. An organizational contingencies view of accounting and information systems implementation. *Accounting, Organizations and Society, 5(4):369*-382, 1980.

[35] Michael J. Ginzberg. Early diagnosis of MIS implementation failure: promising results and unanswered questions. Management Science, 27(4):459–478, April 1981.

[36] Lawrence A. Gordon and Danny Miller. A contingency framework for the design of accounting information systems. Accounting, *Organizations* and *Society,* 1(1):59–69, 1976.

[37] Anthony G. Gorry and Michael S. Scott Morton. A framework for management information systems. In Alfred A. Rappaport, editor, Information *for* decision *making:* readings in cost and managerial accounting, chapter 2, pages 13-26. Prentice-Hall, 3rd edition, 1982. First published in Sloan Management *Review,* Fall 1971.

[38] Joseph F. Hair, Jr., Rolph E. Anderson, Ronald L. Tatham, and William C. Black. *Multivariate* data analysis: *with* readings. Maxwell MacMillan, 3rd edition, 1992.

[39] Leslie Alec. Hayduk. *Structural* equation *modelling with* LISREL. The John Hopkins University Press, 1987.

[40] Stephen J. Hoch and David A. Schkade. A psychological approach to decision support systems. Management Science, 42(1):51–64, January 1996.

[41] Jack T. Hogue and Hugh J. Watson. An examination of decision-makers' utilization of decision support system output. Information *& Management,* 8(4):205–212, April 1985.

[42] Magid Igbaria and Sidney A. Nachman. Correlates of user satisfaction with end user computing: an exploratory study. *Information & Management*, 19:73–82, 1990.

[43] Juhani Iivari and Irja Ervasti. User information satisfaction: IS implementability and effectiveness. *Information & Management*, 27:205–220, 1994.

[44] Blake Ives and Margrethe H. Olson. User involvement and MIS success: a review of research. *Management Science*, 30(5):586–603, May 1984.

[45] Blake Ives, Margrethe H. Olson, and Jack J. Baroudi. The measurement of user information satisfaction. *Communications of the ACM*, 26(10):785–793, October 1983.

[46] Mary C. Jones, G. Stephen Taylor, and Barbara A. Spencer. The CEO/CIO relationship revisited: An empirical assessment of satisfaction with IS. Information & Management, 29:123–130, 1995.

[47] Karl G. Jöreskog and Dag Sörbom. *LISREL7: a guide to the program and applications*. SPSS Inc., 2nd edition, 1989.

[48] Kyung Kyu Kim. Task characteristics, decentralization, and the success of hospital information systems. *Information & Management*, 19:83–93, 1990.

[49] Vincent S. Lai and Edward T. Chen. An assessment of the job prospects of MIS doctoral students in the academic marketplace. *Information & Management*, 29(4):183-189, 1995.

[50] Vincent S. Lai and Bernard Reeh. ISDN implementation in the United States and Germany: a cross-country assessment. *Information & Management*, 29(3):131–140, 1995.

[51] Dennis M.S. Lee, Eileen M. Trauth, and Douglas Farwell. Critical skills and knowledge requirements of IS professionals: a joint academic/industry investigation. *MIS Quarterly*, 19(3):313–340, September 1995.

[52] J. Scott Long. Confirmatory factor analysis: a preface lo LISREL, volume 33 of *Quantitative Applications in the Social Sciences*. Sage University Papers, 1983.

[53] J. Scott Long. *Covariance structure models; an introduction to LISREL*, volume 34 of *Quantitative Applications* in the Social Sciences. Sage University Papers, 1983.

[54] Henry C. Lucas. The evolution of an information system: from key-man to every person. Sloan Management *Review*, pages 39-52, Winter 1978.

[55] Norman B. MacIntosh. A contextual model of information systems. *Accounting, Organizations and Society*, 6(1):39–53, 1981.

[56] Norman B. MacIntosh. *The Social Software of Accounting and Information Systems*. John Wiley & Sons, 1985.

[57] Norman B. MacIntosh and Richard L. Daft. User department technology and information design. *Information & Management*, 1:123–131, 1978.

[58] M. Lynne Markus and Daniel Robey. The organizational validity of management information systems. Human *Relations*, 36(3):203–226, 1983.

[59] Charles H. Mawhinney and Albert L. Lederer. A study of personal computer utilization by managers. *Information & Management*, 18:243–253, 1990.

[SO] Shelby H. McIntyre. An experimental study of the impact of judgment-based marketing models. *Management* Science, 28(1):17–33, January 1982.

[61] James D. McKeen, Tor Guimaraes, and James C. Wetherbe. The relationship between user participation and user satisfaction: an investigation of four contingency factors. *MIS Quarterly*, pages 427-451, December 1994.

[62] Nancy Paule Melone. A theoretical assessment of the user-satisfaction construct in information systems research. Management Science, 36(1):76–91, January 1990.

[63] Ido Millet and Charles H. Mawhinney. Executive information systems: a critical perspective. Information & Management, 23:83–92, 1992.

[64] Henry Mintzberg. Managerial work: analysis from observation. *Management Science*, 18(2):B:92–B:110, October 1971.

[65] Henry Mintzberg. The myths of MIS. *California* Management *Review*, XV(1):92–97, Fall 1972.

[66] Seev Neumann and Michael Hadass. DSS and strategic decisions. *California Management Review*, XXII(2):77–84, Spring 1980.

[67] Jeratta Horn Nord and G. Daryl Nord. Executive information systems: A study and comparative analysis. Information & Management 29:95–106, 1995.

[68] Margrethe H. Olson and Blake Ives. User involvement in systems design: an empirical test of alternative approaches. *Information & Management*, 4(4):183–195, 1981.

[69] Charles A. O'Reilly, III. Variations in decision makers' use of information sources: the impact of quality and accessibility of information. *Academy of Management* Journal, 25(4):756–771, 1982.

[70] J. Michael Pearson and J.P. Shim. An empirical investigation into decision support systems capabilities: a proposed taxonomy. *Information &* Management, 27(1):45-57, 1994.

[71] J. Michael Pearson and J.P. Shim. An empirical investigation into DSS structures and environments. *Decision Support* Systems, 13(2):141–158, 1995.

[72] Michael J. Pearson, Cynthia S. McCahon, and Ross T. Hightower. Total quality management: are information systems managers ready. Information & Management, 29(5):251–263, 1995.

[73] Edward Rivard and Kate Kaiser. The benefit of quality IS. *Datamation*, 35:53–58, January 15 1989.

[74] Daniel Robey. User attitudes and management information system use. *Academy of Management Journal,* 22(3):527–538, 1979.

[75] G. Lawrence Sanders and James F. Courtney. A field study of organizational factors influencing DSS success. *MIS Quarterly*, 9(1):77–93, March 1985.

[76] Ramesh Sharda, Steve H. Barr, and James C. McDonnell. Decision support systems effectiveness: a review and empirical test. Management Science, 34(2):139–159, February 1988.

[77] Herbert A. Simon. The New Science *of Management* Decision, volume III of The *Ford Distinguished Lectures.* Harper & Row, New York/Evanston, 1960.

[78] Sidney R. Snitkin and William R. King. Determinants of the effectiveness of personal decision support systems. *Information & Management,* 10(2):83–90, 1986.

[79] Ashok Subramanian and Sree Nilakanta. Measurement: a blueprint for theory-building in MIS. *Information & Management,* 26:13–20, 1994.

[80] Hervé Thiriez. Towards a DEISS. European Journal *of Operational Research,* 61:72-85, 1992.

[81] Gholamreza Torkzadeh and William J. Doll. The test-retest reliability of user involvement measures. Infownation *& Management,* 26:21–31, 1994.

[82] Efraim Turban. Decision support and *expert systems: management support* systems. Maxwell MacMillan, New York, 2nd edition, 1990.

[83] Robert Urwiler, Narender K. Ramarapu, Ronald B. Wilkes, and Mark N. Frolick. Computer-aided software engineering: the determinants of an effective implementation strategy. Information *& Management,* 29(4):215–225, 1995.

[84] Michael Antal Vasarhelyi. Man-machine planning systems: A cognitive style examination of interactive decision making. Journal *of* Accounting *Research,* 15(1):138-153, Spring 1977.

[85] Andrew H. Van de Ven and Diane L. Ferry. *Measuring and Assessing Organizations.* Series on Organizational Assessment and Change. Wiley, 1980.

[86] George E. Vlahos and Thomas W. Ferratt. Information technology use by managers in Greece to support decision making: amount, perceived value, and satisfaction. *Information & Management*, 29(6):305–315, 1995.

[87] J.R.G. Wood and A.T. Wood-Harper. Information technology in support of individual decision-making. Journal *of* Information *Systems,* 3:85–101, 1993.

[88] Bayard E. Wynne and Gary W. Dickson. Experienced managers' performance in experimental man-machine decision system simulation. *Academy of Management Journal*, 18(1):24–40, March 1975.

[89] Dale Young and Hugh J. Watson. Determinates of EIS acceptance. *Information & Management, 29:* 153-164, 1995.

A Essentials of LISREL notation

All structural equation models in this paper have been estimated using **LISREL 8.** To represent those models the conventional **LISREL** notation and accompanying graphical representation for path models (as described in [47]) have been used. The main aim of this appendix is to introduce this notation. No attempt will be made to give an exhaustive treatment of structural equation modelling.[23]

In a structural equation model the phenomena of prime interest will usually be the (relations between) dependent and independent *latent* variables. In **LISREL** notation the vector of independent variables is labelled $\boldsymbol{\xi}_{b\times 1}$ and the vector of dependent variables is labelled $\boldsymbol{\eta}_{a\times 1}$. The matrix of structural parameters which reflect the influence of the independent on the dependent variables is labelled $\boldsymbol{\Gamma}_{a\times b}$. The matrix of the structural parameters which reflect the mutual relations between the dependent variables is labelled $\mathbf{B}_{a\times a}$. As a consequence, the structural equations are represented by the following equation:

$$\boldsymbol{\eta}_{a\times 1} = \boldsymbol{\Gamma}_{a\times b}\boldsymbol{\xi}_{b\times 1} + \mathbf{B}_{a\times a}\boldsymbol{\eta}_{a\times 1} + \boldsymbol{\zeta}_{a\times 1}$$

In which $\boldsymbol{\zeta}_{a\times 1}$ is the vector of the error terms of the structural equations. The covariance matrix of $\boldsymbol{\zeta}_{a\times 1}$ is labelled $\boldsymbol{\Psi}_{a\times a}$. The covariance of the independent variables is labelled $\boldsymbol{\Phi}_{b\times b}$.

In graphical representations of **LISREL** models all latent variables are represented by circles. The structural parameters are represented by one-headed arrows from the independent to the dependent variables or between the independent variables. The error terms are represented by the single letter ζ_n. An arrow points from the error term to the dependent variable η_n. Covariances among error terms are represented by two-headed arrows between those error terms. All parameters that are supposed to equal zero are omitted from the graphical representation of the model.

Each latent variable is 'measured' by one or more manifest variables (e.g., questions from a measurement instrument). The vector of manifest variables that are used to assess the independent and dependent latent variables are labelled $\mathbf{x}_{d\times 1}$ and $\mathbf{y}_{c\times 1}$, respectively. Each manifest variable is supposed to be a function of one of more latent variables. Latent dependent variables are not allowed to influence manifest independent variables and vice versa.[24] The matrices of the parameters of the functions that determine the manifest variables are labelled respectively $\boldsymbol{\Lambda}^x_{d\times b}$ and $\boldsymbol{\Lambda}^y_{c\times a}$. The elements $\lambda_{m,n}$ of those matrices are called factor loadings. The functions themselves are:

$$\begin{aligned} \mathbf{x}_{d\times 1} &= \boldsymbol{\Lambda}^x_{d\times b}\boldsymbol{\xi}_{b\times 1} + \boldsymbol{\delta}_{d\times 1} \\ \mathbf{y}_{c\times 1} &= \boldsymbol{\Lambda}^y_{c\times a}\boldsymbol{\eta}_{a\times 1} + \boldsymbol{\epsilon}_{c\times 1} \end{aligned}$$

[23] Hair [38] provides an elementary introduction to structural equation modelling. De Long [52, 53] devotes particular attention to confirmatory factor analysis. Hayduk [39] provides a fairly accessible, yet complete treatment of **LISREL.** Bollen [13] contains a more advanced treatment of structural equation modelling, and evidently the work of Jöreskog and Sorbom [47] themselves is of importance.

[24] A researcher may choose to model an independent latent variable as a dependent latent variable because it shares a manifest variable with another dependent variable.

In which $\boldsymbol{\delta}_{d\times 1}$ and $\boldsymbol{\epsilon}_{c\times 1}$ are vectors with the error terms of the measurement model. The matrices $\boldsymbol{\Theta}^{\delta}_{d\times d}$ and $\boldsymbol{\Theta}^{\epsilon}_{c\times c}$ represent the covariances between those error terms.

In a path model the manifest variables are represented by rectangles, and the error terms by single letter δ_n and ϵ_n that are connected with a manifest variable by an arrow from the error term to the manifest variable x_n and y_n, respectively. The factor loadings are represented by arrows from the latent to the manifest variables. As usual parameters supposed to equal zero are omitted from the graphical representation.

Together, the matrices and functions mentioned above imply the following covariance matrix:

$$\mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_{yy} & \mathbf{\Sigma}_{yx} \\ \mathbf{\Sigma}_{xy} & \mathbf{\Sigma}_{xx} \end{bmatrix}$$

The four sub-matrices of this matrix $\mathbf{\Sigma}$ are

$$\begin{aligned} \mathbf{\Sigma}_{xx} &= \mathbf{\Lambda}_x \mathbf{\Phi} \mathbf{\Lambda}'_x + \mathbf{\Theta}_\delta \\ \mathbf{\Sigma}_{yy} &= \mathbf{\Lambda}_y (\mathbf{I} - \mathbf{B})^{-1} (\mathbf{\Gamma}\mathbf{\Phi}\mathbf{\Gamma}' + \mathbf{\Psi})(\mathbf{I} - \mathbf{B}')^{-1} \mathbf{\Lambda}'_y + \mathbf{\Theta}_\epsilon \\ \mathbf{\Sigma}_{xy} &= \mathbf{\Lambda}_x \mathbf{\Phi} \mathbf{\Gamma}' (\mathbf{I} - \mathbf{B}')^{-1} \mathbf{\Lambda}'_y \\ \mathbf{\Sigma}_{yx} &= \mathbf{\Lambda}_y (\mathbf{I} - \mathbf{B})^{-1} \mathbf{\Gamma} \mathbf{\Phi} \mathbf{\Lambda}'_x \end{aligned}$$

It is possible to obtain estimates for the parameters of this model by optimizing a fit function, which will usually be a function of both the observed covariance matrix S and the implied covariance matrix $\mathbf{\Sigma}$. In the analyses in this paper maximum likelihood estimation has been used, which requires that the following fit-function F be minimized by iterative adjustment of the free elements of $\mathbf{B}$, $\mathbf{\Gamma}$, $\mathbf{\Lambda}_x$, $\mathbf{\Lambda}_y$, $\mathbf{\Phi}$ and $\mathbf{\Psi}$:

$$F = \log \|\mathbf{\Sigma}\| + \mathrm{trace}(\mathbf{S}\mathbf{\Sigma}^{-1}) - \log \|\mathbf{S}\| - (c + d)$$

B Response rates in MIS research

In order to allow the reader to compare the response rate obtained in this study with previous research, data on surveys administered to managers and staff members were collected from volume 19 (1995) of MISQ and volume 29 (1995) of *Information & Management*. Compeau and Higgins [17] obtained a 53.4% response rate from a sample frame that consisted 'primarily' of managers, however, 30% of their respondents occupied a managerial position, indicating that the response among managers was relatively low and delegation to non-managers high. Lee, Trauth, and Farwell [51] report separate response rates of 42.3%, 13.0% and 20.7% for IS managers, user managers and IS consultants, respectively. Ang, Sum, and Chung [4] report a 17% response rate. Chau [15] addressed his questionnaire to 'the responsible person' in the organization-this way of addressing is likely to increase delegation and, as a consequence, response rates-and reports a 24.4% response rate. Nord and Nord [67] asked the CEOs in their sample 'to fill out the questionnaire or forward it to another executive' [67, p. 97]. They obtain a 30.4% response rate for a three-page questionnaire and, according to their own report, have only managers among their respondents. Sixty-one CEOs and fourty-seven CIOS out of 750 returned a questionnaire sent out by Jones, Taylor, and Spencer [46]. Lai and Reeh [50] do not report response rates, but they may be derived from the number of observations in tabularized material. Response rates for the USA and Germany were 8.2% and 7.2%, respectively. Young and Watson [89] report a 57.4% response rate, but of their respondents only 3.7% indicated that they occupied a managerial position, furthermore only 81 out of 128 responses were used for analyses-the number of refusals probably was high. Lai and Chen [49] report a 39.1% response rate in a study among MIS candidates. Urwiler et al. [83] did a survey among 200 software development professionals and obtained 70 responses. Pearson, McCahon, and Hightower [72] report 25.9% total and 22.7% useful responses. Vlahos and Ferratt [86], finally indicate that they sent out 'approximately' 1,000 questionnaires and obtained 55 responses.

C Data used for the LISREL analyses

This appendix contains the Spearman rank correlation matrix used for the **LISREL** analyses presented in this paper. Under each correlation coefficient the number of observations it has been based upon is presented. *The* data *presented in this* appendix may only *be used to* replicate *the analyses presented in this* paper. *Any other* usage requires *written permission of the author.*

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.
1. Cont1	1.000																												
	103																												
2. Cont2	0.840	1.000																											
	103	103																											
3. Cont3	0.737	0.739	1.000																										
	103	103	103																										
4. Cont4	0.692	0.703	0.669	1.000																									
	102	102	102	102																									
5. Acc1	0.639	0.588	0.582	0.698	1.000																								
	103	103	103	102	103																								
6. Acc2	0.636	0.632	0.598	0.745	0.891	1.000																							
	103	103	103	102	103	103																							
7. Acc3	0.578	0.603	0.551	0.651	0.822	0.878	1.000																						
	103	103	103	102	103	103	103																						
8. Acc4	0.639	0.610	0.586	0.658	0.841	0.874	0.917	1.000																					
	103	103	103	102	103	103	103	103																					
9. Form1	0.571	0.577	0.647	0.575	0.500	0.502	0.457	0.535	1.000																				
	103	103	103	102	103	103	103	103	103																				
10. Form2	0.602	0.593	0.696	0.579	0.516	0.555	0.497	0.573	0.847	1.000																			
	103	103	103	102	103	103	103	103	103	103																			
11. Form3	0.543	0.601	0.616	0.587	0.476	0.532	0.508	0.559	0.831	0.805	1.000																		
	103	103	103	102	103	103	103	103	103	103	103																		
12. Form4	0.458	0.482	0.580	0.529	0.478	0.552	0.487	0.514	0.749	0.742	0.757	1.000																	
	103	103	103	102	103	103	103	103	103	103	103	103																	
13. Time1	0.488	0.530	0.578	0.668	0.628	0.684	0.674	0.667	0.538	0.546	0.516	0.571	1.000																
	103	103	103	102	103	103	103	103	103	103	103	103	103																
14. Time2	0.431	0.505	0.530	0.560	0.614	0.657	0.671	0.721	0.411	0.453	0.419	0.436	0.778	1.000															
	103	103	103	102	103	103	103	103	103	103	103	103	103	103															
15. Time3	0.391	0.436	0.382	0.507	0.623	0.643	0.627	0.692	0.306	0.398	0.372	0.396	0.687	0.825	1.000														
	103	103	103	102	103	103	103	103	103	103	103	103	103	103	103														
16. Time4	0.389	0.478	0.447	0.522	0.503	0.605	0.588	0.626	0.365	0.464	0.384	0.446	0.705	0.832	0.837	1.000													
	103	103	103	102	103	103	103	103	103	103	103	103	103	103	103	103													
17. EOU1	0.499	0.488	0.567	0.538	0.544	0.585	0.530	0.561	0.624	0.645	0.677	0.614	0.519	0.472	0.346	0.467	1.000												
	103	103	103	102	103	103	103	103	103	103	103	103	103	103	103	103	103												
18. EOU2	0.490	0.485	0.585	0.513	0.520	0.549	0.538	0.561	0.643	0.650	0.669	0.646	0.525	0.487	0.372	0.464	0.924	1.000											
	103	103	103	102	103	103	103	103	103	103	103	103	103	103	103	103	103	103											
19. EOU3	0.569	0.550	0.666	0.620	0.630	0.639	0.627	0.635	0.647	0.679	0.660	0.646	0.627	0.579	0.499	0.526	0.779	0.826	1.000										
	103	103	103	102	103	103	103	103	103	103	103	103	103	103	103	103	103	103	103										
20. Diff1	-0.133	-0.078	-0.118	-0.070	-0.062	-0.035	0.084	0.065	-0.039	-0.147	-0.020	-0.081	-0.165	-0.115	-0.171	-0.283	-0.146	-0.209	-0.071	1.000									
	49	49	49	49	40	49	49	49	49	49	49	49	49	49	49	49	49	49	49	86									
21. Diff2	0.037	0.065	0.070	0.051	-0.049	-0.043	-0.022	-0.010	-0.068	-0.156	-0.092	-0.065	-0.111	-0.133	-0.063	-0.149	-0.121	-0.225	-0.058	0.398	1.000								
	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	85	85								
22. Diff3	-0.153	-0.240	-0.183	-0.055	-0.123	-0.097	-0.033	-0.104	-0.178	-0.151	-0.108	-0.216	-0.283	-0.313	-0.227	-0.292	-0.087	-0.203	-0.115	0.213	0.244	1.000							
	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	86	85	86							
23. Diff4	-0.171	-0.245	-0.133	-0.212	-0.113	-0.124	-0.128	-0.174	-0.313	-0.313	-0.297	-0.330	-0.315	-0.256	-0.172	-0.274	-0.181	-0.309	-0.143	0.295	0.307	0.466	1.000						
	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	86	85	86	86						
24. Var1	0.055	0.103	0.046	0.023	-0.063	-0.138	-0.058	-0.044	-0.073	-0.100	-0.128	-0.113	-0.074	-0.137	-0.138	-0.205	-0.226	-0.238	-0.153	0.073	0.260	0.211	0.217	1.000					
	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	85	84	85	85	85					
25. Var2	0.101	0.043	0.063	0.155	0.015	-0.023	-0.075	-0.026	0.013	0.073	0.012	-0.068	0.035	0.045	0.014	-0.062	-0.035	-0.073	-0.103	0.048	0.075	0.258	0.015	0.465	1.000				
	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	86	85	86	86	85	86				
26. Var3	0.061	0.075	-0.072	0.007	0.126	0.059	0.112	0.063	-0.070	-0.014	-0.117	-0.175	-0.066	0.027	0.016	-0.010	0.089	-0.047	-0.050	0.096	0.039	0.328	0.227	0.453	0.496	1.000			
	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	84	83	84	84	83	84	84			
27. Var4	-0.128	-0.045	-0.019	0.099	-0.041	-0.050	-0.007	-0.005	0.195	0.102	0.146	0.121	0.164	0.007	-0.080	-0.083	-0.089	-0.125	0.075	0.143	0.243	0.062	0.081	0.338	0.151	0.142	1.000		
	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	86	85	86	86	85	86	84	86		
28. Little	0.074	-0.064	0.019	0.046	0.128	0.048	0.075	0.032	0.033	0.016	-0.050	-0.074	0.078	0.062	0.107	0.056	0.015	-0.016	-0.012	-0.009	0.102	0.106	0.061	-0.099	-0.101	0.052	0.083	1.000	
	99	99	99	98	99	99	99	99	99	99	99	99	99	99	99	99	99	99	99	85	84	85	85	84	85	84	85	165	
29. Wrong	0.210	0.333	0.316	0.284	0.159	0.157	0.159	0.210	0.294	0.282	0.276	0.197	0.282	0.197	0.121	0.152	0.246	0.185	0.192	0.000	-0.072	-0.076	-0.071	-0.053	-0.015	-0.059	0.162	-0.066	1.000
	99	99	99	98	99	99	99	99	99	99	99	99	99	99	99	99	99	99	99	85	84	85	85	84	85	84	85	165	165