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ABSTRACT: A latent variable approach to the evaluation of CASE tools is used to assess user needs and applications. Responses are consistent with the taxonomy of upper and lower CASE tools. Results indicate the importance of analysis and prototyping features. Some existing tools are rated significantly higher than others in terms of these features. The study also reveals a link between organizational size and the demand for upper and lower CASE tool features. Smaller organizations use CASE tools in the design stage and rely on teamwork and collaboration facilities. Larger firms focus on lower CASE facilities such as prototyping to build completed systems.

KEY WORDS AND PHRASES: computer-aided software engineering, CASE, CASE tool ratings, path analysis, structural equation.

COMPUTER SOFTWARE APPLICATIONS ARE SOME OF THE MOST COMPLEX products marketed today. With many different attributes and applications, it is challenging to evaluate the various products within any given software category. If a developer/vendor

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misjudges the market demands, both the vendor and subsequent buyers may suffer. This gap has been particularly acute in the development of Computer-Aided Software Engineering (CASE) tools.

Since the introduction of CASE tools, there has been uncertainty about the demand for the tools. As development methodologies evolved, it was difficult to determine what features of the tools could be used to improve the software development process. CASE tools eventually gained a reputation of not fulfilling their promises [6, 7].

Despite limited success and substantial industry changes, many application developers (buyers) are convinced that CASE tools improve the overall systems development process [6]. The question faced by software developers is: What features of CASE tools are considered useful? From the vendor's perspective, answers to this question can be used to improve CASE tools. From the perspective of MIS managers and developers, answers to the question can be used to improve the software development process.

One way to answer the question and determine which CASE tool features are used by software developers is to ask these developers to evaluate the CASE tools that they use. By identifying the features that developers find important, we gain a better understanding of how CASE tools support the development process. Latent variables and path analysis provide the tools to analyze the various relationships.

Literature Review

COMMUNICATION AND MEASUREMENT ARE IMPORTANT ISSUES in survey research. The primary constraint is that it is not possible to observe an individual's true impressions. In fact, people may not be able to assess their own impressions accurately. There are various solutions to this problem, each potential solution uses slightly different assumptions, collects different types of data, and has varying objectives.

With complex software, such as CASE tools, one of the objectives of this study is to divide product features into categories and evaluate the strength of the relationships between the categories. A latent variable approach is the most useful method for accomplishing this.

The latent variable approach is based on the idea that people have some internal valuation or ability. In the situation of evaluating CASE tools, developers/buyers conduct an internal evaluation of the various attributes of particular CASE tools. This item is latent and cannot be observed directly. A survey can provide a measure, but it will never be exact. The statistical approach is to collect data from multiple respondents. Responses to individual features provide estimates of the latent variable. Structural equation relationships can then be estimated among the various latent variables.

Structural equations and latent variables are useful techniques for handling data with measurement errors. The latent variables (factors) can be estimated from the observed responses on each item. The structural relationships among the latent variables are statistically more reliable than using the observed values.

CASE Attributes

Basic CASE attributes were identified from prior research [4, 5, 13], from initial interviews with CASE users, and from feedback provided during pretesting of the survey instrument. Extensive discussions were held with software developers during the pretesting process to ascertain specific CASE tool features and associated attributes correctly.

Several earlier studies have examined various attributes of CASE tools. For example, Norman and Nunamaker [9] examined features of a single CASE tool using pairwise rankings of seventeen features that were analyzed with traditional multidimensional scaling and cluster techniques. They concluded that software designers had improved their development output with the use of CASE tools. The importance of advanced CASE features are highlighted by Forte and Norman [3], including collaborative tools, internal help systems and "advisors," and prototyping capabilities with respect to CASE usage and acceptance.

Kemerer [5] found that, as CASE tools stay within an organization, their usage declines rapidly after the first year. In certain organizations, upwards of 70 percent of the CASE products are not in use beyond the first year. This result can be partially explained by the relative complexity of CASE tools and the level of training provided to users that precludes usage by systems professionals. More recently, Iivari [4] reports that the perceived complexity of the CASE tools was a significant reason for reduced effectiveness of continued CASE tool usage.

A common technique in evaluating software is to focus on one or two elements in isolation. For research considerations, there is nothing inherently wrong with this approach, as long as the results are not used as a basis for judgments about the relative merits of the software packages. For example, a study by Vessey and Sravanapudi [13] focused on the use of CASE tools for collaboration. This method relied on predefined categories and averages of user responses to evaluate CASE features such as testing for inconsistencies, providing methodology prompts within the graphics section, and visual presentation of analyses. A detailed evaluation of individual product features was not done.

Upon evaluation of prior studies, comprehensive pretesting, and software developer interviews, six basic categories of CASE tool features were identified. Product features fall into the following categories: graphics, prototyping, data dictionary, design analysis, code generation, and general features (e.g., price and vendor support). These categories accommodate the classification of tools into upper CASE and lower CASE attributes. The graphics, data dictionary, and design analysis fit into the upper CASE taxonomy, which consists of the early (analysis) design stages that define the project. The prototyping and code generation features comprise lower CASE or developmental side classification. Each category contains detailed features—yielding fifty-one items. (The items are listed later in Table 5, along with the abbreviations used in the subsequent figures.)

Latent Variable Model

The latent variable approach was designed to identify relationships between variables that can only be observed indirectly—especially with survey measures. Basic theory and implications are presented by Loehlin [8]. The various uses and interpretations of latent variable analysis are examined by Arbuckle [1]. Both writers focus on the path analysis techniques used in this study.

This study was designed to facilitate two levels of analysis. First, the individual fifty-one features are important. Or, more correctly, some of the items are more important than others. It is useful to understand which items are more important than the others from a tool-user perspective. On a second level, the relationships between the categories provide information about the tools. These relationships also provide information about how these tools are used in the software development process. For example, if the respondents highly valued graphics features and placed no importance on analysis and coding, it would indicate that the tools were being used for upper CASE design, but not for lower CASE development.

Existing CASE tool features are grouped into six categories, and there is one latent variable for each category. A seventh latent variable consists of the overall evaluation of the tool. Two sets of relationships among the factor variables are important. First, a structural equation reveals how the total evaluation of a CASE tool is composed of the evaluations from each category. Second, the structural relationship between the categories and the total tool (product) evaluation, along with the correlations between the category variables will identify tradeoffs between the categories. The structural correlations between the latent variables are displayed in figure 1. (To avoid cluttering the diagram, the correlations between the category variables are not shown.) There are pairwise correlations between each of the six latent variables that generate a total of fifteen correlations.

Personal factors such as education, experience, and company size might also affect the overall evaluation and this set of factors needs to be considered in the analysis scheme. It is also necessary to control for the effect of different tools. By including this variable in the analysis, this relationship was tested for significant differences in the tools being investigated.

A set of latent variables is derived from the relationship with the individual item responses. Figures 2 through 7 show the traditional path analysis relationships defined for the category variables. The coefficients reported on the graphs are the factor loadings of the individual items. Statistical significance is indicated by asterisks. One asterisk represents significance at 5 percent and two at a 1 percent level. Finally, note that some of the items within a factor are correlated. To prevent clutter, only the significant correlations are shown in the figures.

Figures 1 through 7 present the individual components of the model. In actuality, these components are combined and estimated in one comprehensive model. This approach provides for a better estimation process and further supports the investigation of more item details. However, the model and results are displayed in sections to make it easier to read the individual components.

Survey

Systems professionals identified as CASE users became the sample group. Participants were chosen randomly from firms that were current CASE tool product users.

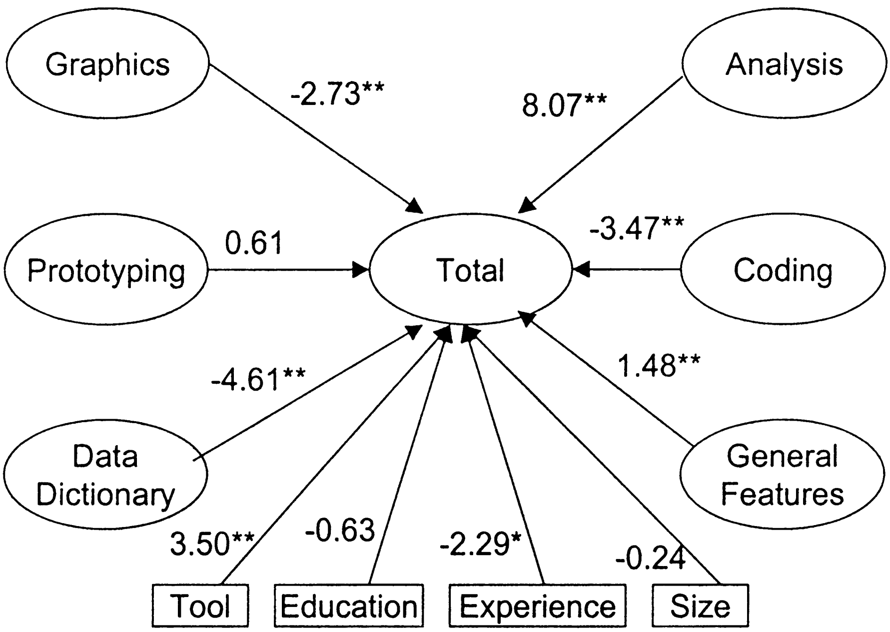

Figure 1. Structural Relationships of Latent Variables.
Parameters are standardized structural coefficients, with 1% significance indicated by two asterisks and 5% by one asterisk. Correlations among the six categorical latent variables are given in Table 4.

Specific systems development user groups that were characterized as CASE-interested aided in the sample selection process. One hundred and eight surveys were completed (from a distribution of 350), and ninety-seven were deemed usable for data analysis. Surveys were mailed or distributed by FAX to organizations identified as CASE tool users; a few instruments were administered via direct interviews. Participants were asked to evaluate specific CASE tools in terms of the features they use.

Respondents

The primary target of this survey was systems analysts and developers at organizations who used CASE tools in their day-to-day jobs. There were a total of seventy-six respondents, representing seventy-one different organizations. Of this group, eighteen participants compared more than one product, and three people compared three products (for a total of ninety-seven evaluations). It was our intention in this study to broaden the respondent pool and minimize surveying multiple users within a particular firm. Almost all of the respondents have at least a bachelor's degree (sixty-four), and twenty-one have a graduate or postgraduate degree. The average experience with CASE tools is approximately 3.5 years; the majority (sixty-seven) have between one and six years experience. Overall, the respondents have spent an average of five years in their present positions. In general, the respondents are highly educated, with

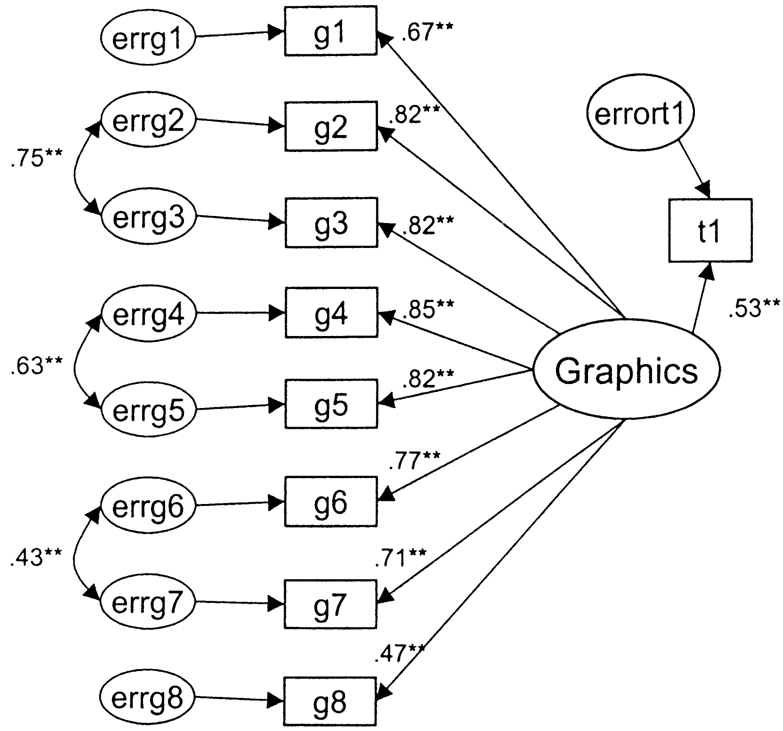

Figure 2. Graphics Latent Variable Relationship to Detail Items.
The coefficients are factor loadings. Asterisks represent statistical significance, where two denote a 1% level and one is a 5% level.

considerable experience and knowledge of CASE tools. Table 1 shows that respondents evaluated a total of thirteen different products, with the majority of responses involving Texas Instruments' IEF (forty-nine) and ADW (fifteen). (Both ADW and IEF are now products of Sterling Software.) CASE tool users reported on the most current versions of their tool to avoid confounding.

Reliability

While it is theoretically impossible to guarantee that any survey instrument actually achieves its goals, it is common to test for internal consistency of responses. As explained in detail by Peter [11], Cronbach's alpha [2] is generally considered to provide a reasonable estimate of internal consistency.

This survey was designed for two methods of analyzing reliability. Internal consistency can be measured first within each product feature section (graphics, prototyping, etc.), and second across the entire instrument. The reliability estimates are presented in Table 2. For basic research interpretations, Nunally [10] suggests that alpha values of 0.80 are good, while values of 0.90 are preferred for applied survey instruments. Based on these values, the results for this instrument indicate a high level of reliability.

Construct validity is measured by the item correlation with the total. The low and

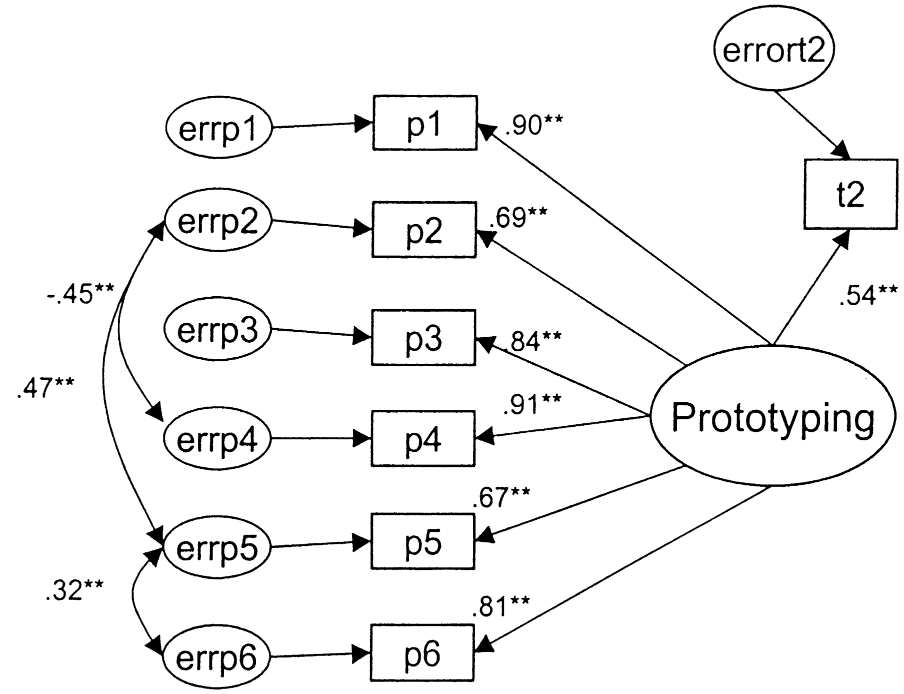

Figure 3. Prototyping Latent Variable Relationship to Detail Items

high correlations for items within each category are shown in Table 2. The values indicate that respondents were relatively consistent within each category. The experience level of the respondents and the attention they gave the survey contributed to the high consistency and high reliability.

For confirmation of discriminant and convergent validity, the study was also evaluated with factor analysis. The results initially indicated twelve potential factors, but the four lowest (total sum of squared loading less than 1.5) contained no significant items, so they were dropped. There is marginal evidence that the data dictionary and general features categories could each be split into two factors—but these two extra factors contained few items and showed no interesting results or correlations. Consequently, only six factors need to be used to describe the various items. In addition, of all fifty-one factors, only two indicated any cross-factor importance. The A4 item (prompting within graphs) had a 0.483 coefficient from the graphics factor. The D1 item (ease of use) had a 0.543 coefficient from the analysis factor. More important, from the original path analysis results (shown in figures 2–7), the factor loadings are very strong and generally significant at a 1 percent level (even for the A4 and D1 coefficients).

Results

THE BASIC RESULTS INDICATE THAT THERE ARE SUBSTANTIAL DIFFERENCES among CASE tools. From the perspective of individual attributes, and from the statistical

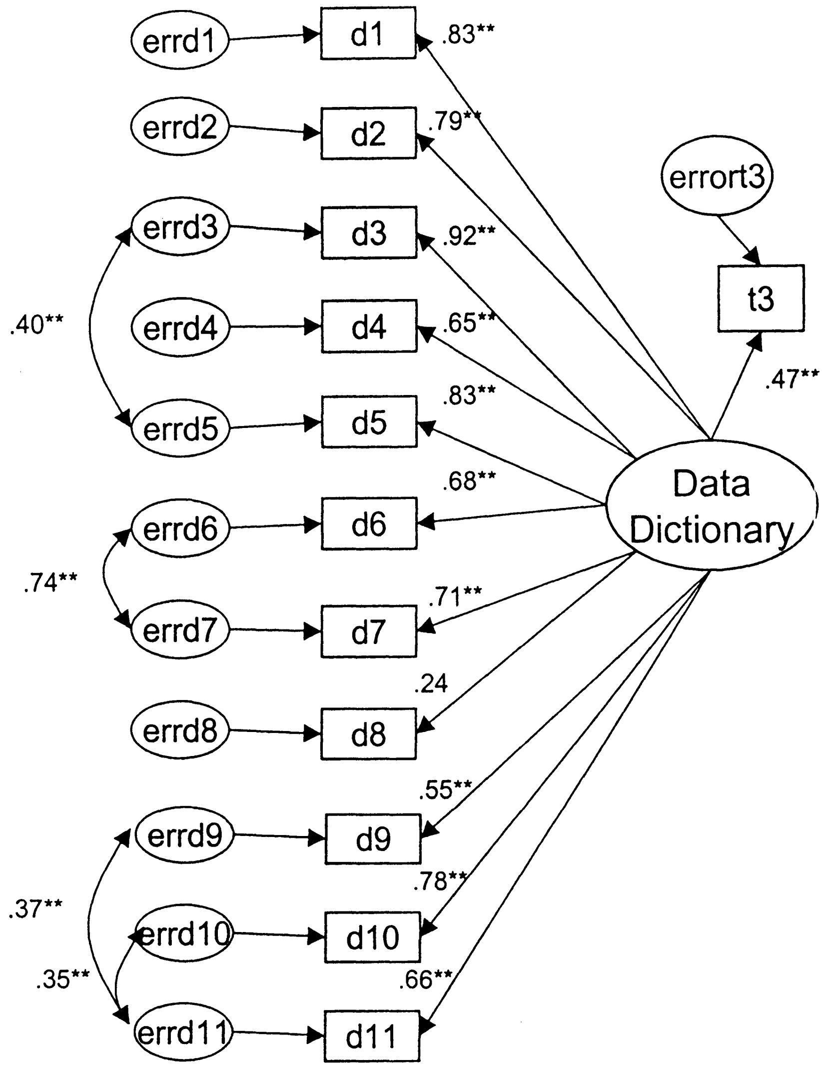

Figure 4. Data Dictionary Latent Variable Relationship to Detail Items

relationships, it is clear that some of the tools obtain significantly higher ratings. First, in general terms, some products are rated higher than the others. Second, even among the higher-rated products, there are differences between the various categories. That is, the individual products exhibit specific strengths and weaknesses. This result is not surprising, given the broad range of products sampled and the degree of experience of the participants.

Attribute Valuation

To highlight the CASE tool differences, average product ratings are displayed in figures 8 through 13. Of particular interest is that some of the tools consistently rate

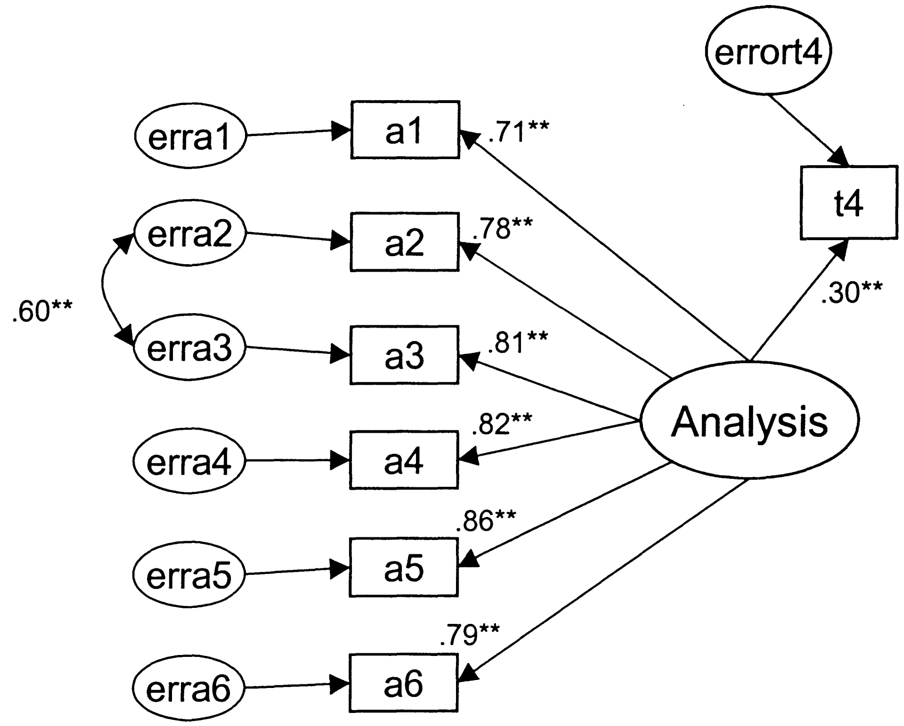

Figure 5. Analysis Latent Variable Relationship to Detail Items

lower than the others (e.g., Pacbase and Transform). Second, while Knowledgeware and Excelerator rate relatively high in graphics, IEF consistently rates higher in analysis and coding features.

From the perspective of overall needs, examine the means across all of the products (heavier line on the graphs). In general, most graphics features were not dependent on the CASE tool. However, the last item (G8: ability to export to other formats) was consistently rated lower in all of the tools—implying that software developers need the ability to integrate CASE diagrams with other tools. Similar data exchange issues were raised in terms of the data dictionary (D6 and D7) features as well.

Most of the products received lower ratings in the analysis, prototyping, and coding categories. User concerns identified for these features include capabilities of the prototyping report writers, and the ease of modifying generated code.

If we looking at means in figure 13, price (F9) appears to be an issue with some of the tools within the general features category. However, there is so much variability that none of the general feature differences is statistically significant. In addition, the general features category has a positive relationship to the overall evaluation (figure 1). Hence, the other factors (e.g., vendor support and longevity) outweigh any price issues.

Before vendors rejoice and interpret this result as a sign to raise prices, two factors must be considered. First, the high variability could indicate that price is an issue to some people. Second, particularly in larger organizations, the respondents evaluating

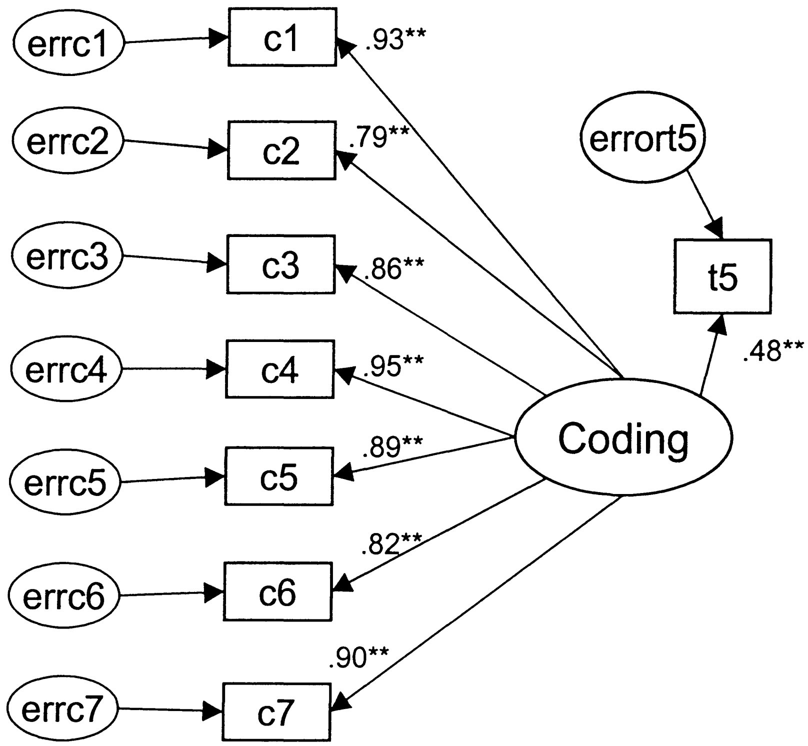

Figure 6. Coding Latent Variable Relationship to Detail Items

the tools are probably not the ones responsible for purchasing the product. It is likely that the purchase decision pertaining to a particular tool may be price-driven from the management perspective. Detailed sensitivity studies would be required to make a final determination regarding the influence that price has on CASE tool purchasing, given the complexity of the buying process.

Latent Variable Results

Latent variable analysis results are reported in figures 1 through 7. The majority of the coefficients are significant at a 1 percent error level. Goodness-of-fit measures indicate that the individual subsections of the model are accurate. (When computed separately, all of the individual section chi-square values are significant.) With the full model, the chi-square value is not significant (probability = 0.00), but this result is typical of these types of models. With large degrees of freedom, the chi-square value increases rapidly (e.g., [1, p. 554]). The CMIN ratio of 2.22 indicates that the model is acceptable.

Three distinct sets of results are elicited from the latent variable approach: (1) the effect of the category variables on the overall evaluation; (2) the impact of personal

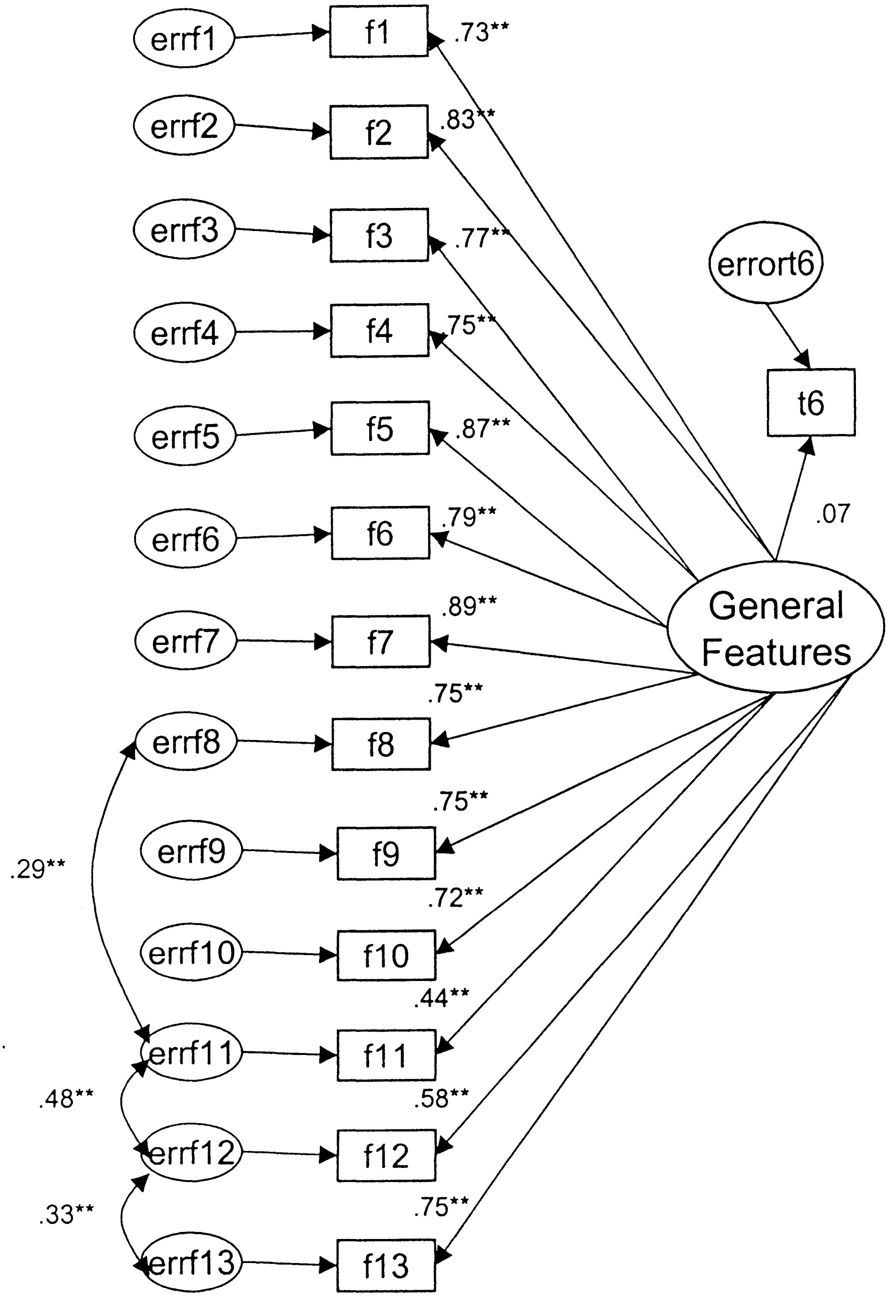

Figure 7. General Features Latent Variable Relationship to Detail Items

Table 1. Number of Responses for Each Tool

Responses	Tool
49	IEF/Texas Instruments
15	ADW
10	Pacbase
6	Excelerator
5	Oracle
3	Transform
2	Bachman
2	Fourgen
1	Huron
1	Merise
1	Synon
1	System Architect
1	Time Line
97	

Table 2. Reliability of the Survey Instrument

	Cronbach's alpha	Construct validity
Graphics features	0.913	0.54–0.84
Prototyping	0.912	0.69–0.84
Data dictionary	0.833	0.51–0.74
Design analysis	0.863	0.67–0.83
Coding	0.907	0.72–0.88
General features	0.912	0.48–0.83
Feature importance	0.881	0.72–0.88
Overall (all items)	0.942	0.32–0.67

factors on the overall results and the product categories; and (3) the correlations between the category variables.

Overall Tool Evaluation

Structural relationships between the categories and the overall evaluation are shown in figure 1. These relationships indicate how each category affects the respondent's overall view of the CASE tool. Most of the coefficients have a significant effect (at a 1 percent error level—as indicated by two asterisks). The one exception is the prototyping category, which is not significant. This latter result implies that CASE tool users are not using the tools for prototyping—they are focusing on other design issues.

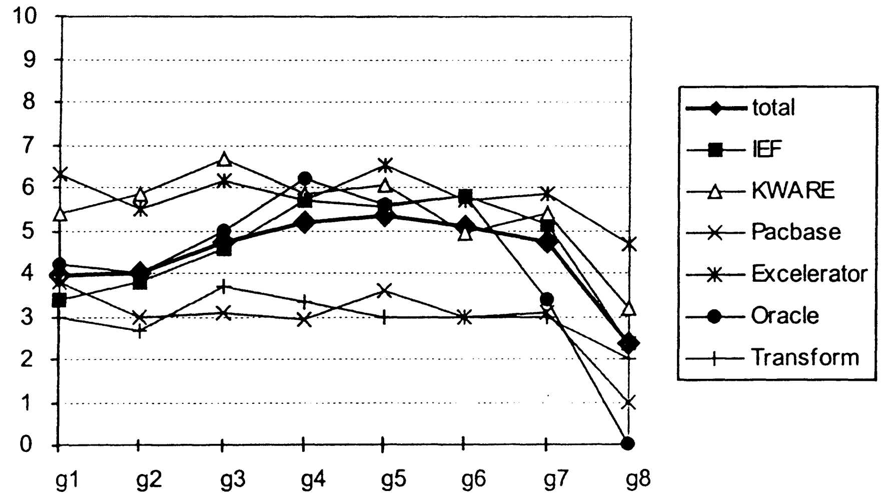

Figure 8. Graphics Features: Average Ratings

The most interesting result is that three of the six coefficients are significantly negative. In other words, receiving a higher evaluation in graphics, data dictionary, and coding features results in a lower overall evaluation. It makes no sense to assume that these categories "cause" a lower overall evaluation. Instead, it is more reasonable to note that respondents are clearly interested in the analysis features. Tools that are strong in this area receive high overall evaluations. Conversely, tools that are weak in analysis features are perceived to be stronger in the other areas (notably graphics and data dictionary).

On the positive side, the analysis category has a strong effect on the overall impression. General features also have a positive impact, and prototyping is positive but not significant. If we look at the associated figures for analysis (figure 5) and general features (figure 7), three detail items in each category are closely associated with the category's latent valuation. In analysis, data normalization, automated prompting within graphics, and visual display of design analysis are important attributes. In general, features, network support, compatibility across versions, and customization are important issues.

Overall, respondents perceive two types of CASE tools: (1) those that are strong in graphics and data dictionary features, versus (2) those that are strong in analysis. The respondents exhibit a clear preference for the tools that are strong in analysis. From the latent variable correlations, it is clear that the tools strong in analysis are also strong in the graphics and data dictionary categories. However, it is the superiority of the analysis facilities that receives the greatest valuation.

Personal Factors

Personal factor effects on the overall evaluation are also displayed in figure 1. Only two of the items are significant (tool at 1 percent and experience at 5 percent). The

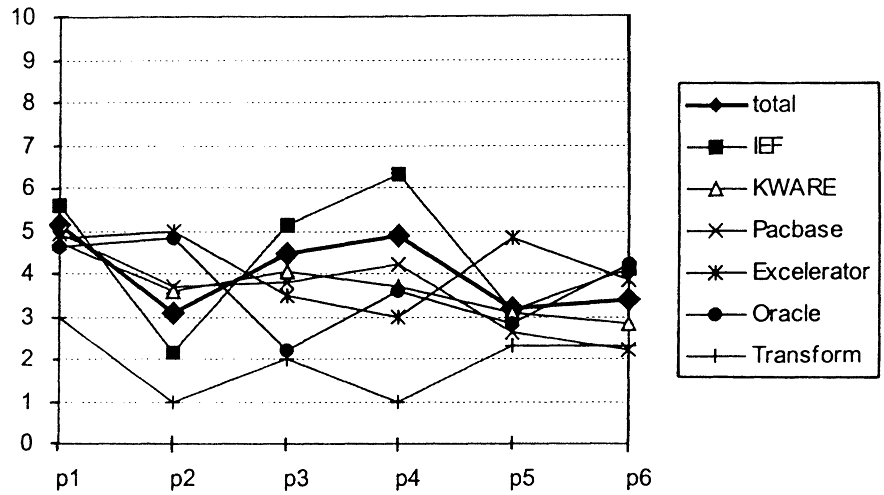

Figure 9. Prototyping Features: Average Ratings

significance on the tool coefficient demonstrates that the evaluations between the tools are significant. Coefficient signs are not relevant because the tools were arbitrarily assigned dummy values. In other words, some tools are clearly considered more useful than others.

The latency coefficient pertaining to the experience variable raises some intriguing issues. The results indicate the effect of experience on the overall evaluation of CASE tools. The conclusion is that the sign of the coefficient is negative. That is, more experienced developers tend to have lower opinions of the value of the CASE tools. It is not clear whether this dissatisfaction represents disillusionment with the tools or a lack of demand for the CASE tool capabilities because more experienced users have found other design techniques to facilitate their work.

Educational level and organizational size coefficients are also negative, but their overall effect is not significant. The education values are correlated with experience and would likely have the same interpretation. The size coefficient, although not significant here, raises some interesting aspects of interpretation. If it truly is negative, then software developers at larger firms see less value in the use of CASE tools. It would seem more reasonable that firm size should be a positive effect: Larger firms would have more need for the design standards, documentation, and teamwork enhancement provided with existing CASE tools.

As shown in Table 3, personal factors are also correlated with the individual category latent variables. Because of the relatively high variability, most of the coefficients are not significant for the graphics category. However, the correlations are significant for all of the other categories. Again, the tool results are not surprising: Even at the level of individual categories, the tools have different ratings.

On the other hand, education, experience, and size all show negative correlations

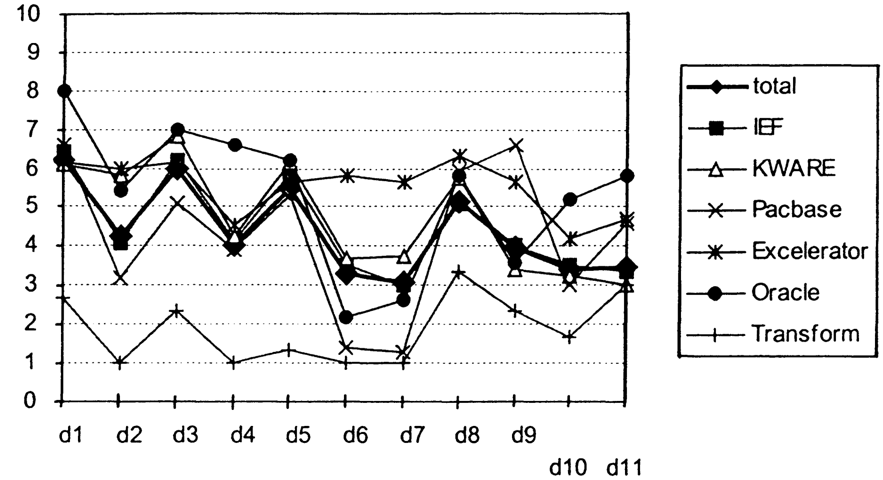

Figure 10. Data Dictionary: Average Ratings

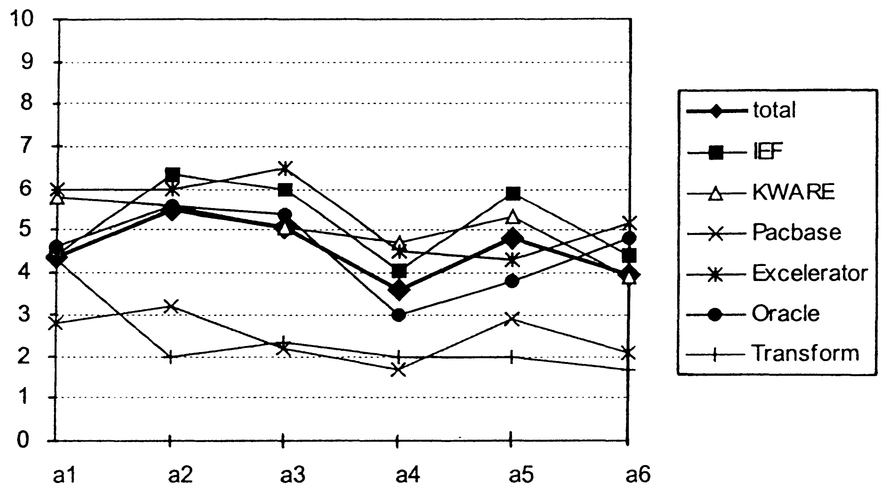

Figure 11. Analysis and Design Features: Average Ratings

with each category—just as implied by the overall rating. In this case, all of the coefficients (except graphics) are significant. These results are contrary to common expectations. CASE tool users with more education and experience have lower valuations of existing CASE tools. The effect of the firm size is the most surprising, since CASE tools would seem to have more value in larger organizations.

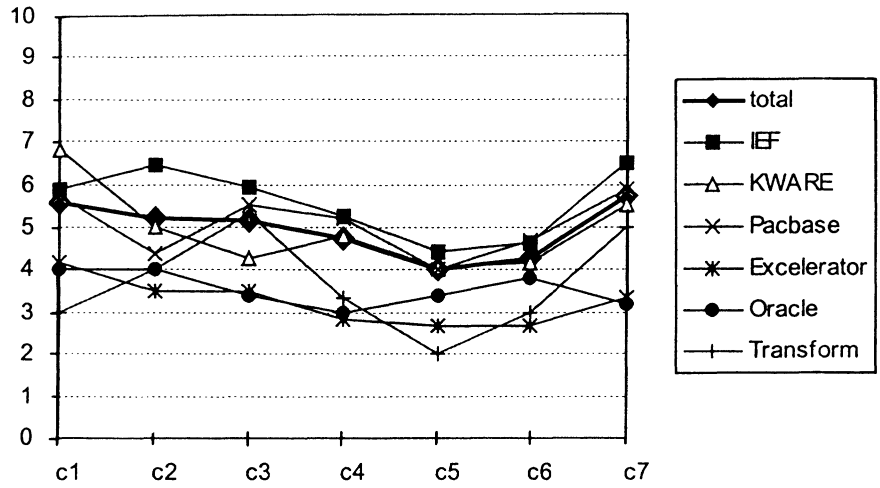

Figure 12. Coding Features: Average Ratings

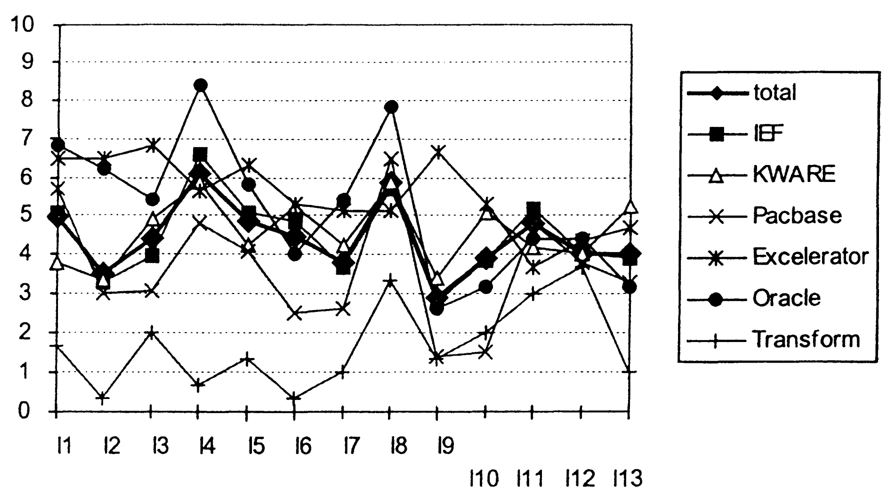

Figure 13. General Features: Average Ratings

Table 3. Effect of Personal Characteristics on Category Evaluations

	Education	Experience	Size	Tool
Graphics	–0.20	–0.20	–0.15	–0.26*
Prototyping	–0.64**	–0.63**	–0.33**	–0.67**
Dictionary	–0.71**	–0.69**	–0.42**	–0.73**
Analysis	–0.68**	–0.69**	–0.39**	–0.77**
Coding	–0.74**	–0.75**	–0.39**	–0.75**
General	–0.66**	–0.57**	–0.33**	–0.66**

Table 4. Correlations Between Categories

	Graphics	Proto.	Dict.	Analysis	Coding	General
Graphics						
Prototyping	0.21					
Data dict.	0.39**	0.77**				
Analysis	0.63**	0.70**	0.90**			
Coding	0.23	0.69**	0.72**	0.81**		
General	0.41**	0.63**	0.76**	0.71**	0.69**	

Correlations Between Categories

It is reasonable to believe that evaluations of each category would be correlated, and the results in Table 4 indicate that most of the categories do show significant correlations with each other. Keep in mind that these are correlations between the latent variables, that is, the perceived valuation for each category. It is not the same as the correlation between observed responses, which could be directly affected by a rating scheme chosen by hurried respondents. The correlations shown in Table 4 measure the relationship between the demands for each category of features.

All of the coefficients are positive, and most are significant at the 0.01 level. For example, there is a 90 percent correlation between the data dictionary and analysis ratings. This relatively high value makes sense, because analysis can only be performed if adequate information is collected in the data repository. Conversely, most of the correlations with the graphics category are lower. In fact, prototyping and coding features are not significantly correlated with the graphics valuation. The basic interpretation is that prototyping and coding do not rely heavily on graphics capabilities. This interpretation seems reasonable when dealing with traditional COBOL transaction systems. Perhaps when CASE tools are extended to "visual" programming languages, the relationships will change.

When structural relationships are examined between the actual ratings (versus the latent variables), the correlations are similar (but not displayed). The one important exception is a significantly negative relationship between graphics and coding fea-

Table 5. Item Descriptions

Upper CASE	Graphics	G1	Support for different structured techniques
		G2	Variety of graph types
		G3	Consistency across graph types
		G4	General ease of use
		G5	Ease of making changes
		G6	Print quality
		G7	Printer support
		G8	Export facilities to other formats
	Data dictionary	D1	Ease of use
		D2	Accessibility from graphs
		D3	Variety and quality of data stored
		D4	Ability to customize
		D5	Depth of description
		D6	Export capabilities to other software
		D7	Import capabilities
		D8	Multiuser access, locking
		D9	History of changes/audit trail
		D10	Support for synonyms
		D11	Contention resolution
	Analysis	A1	Support for different structured techniques
		A2	Ability to find inconsistencies
		A3	Data normalization capabilities
		A4	Prompting capabilities within graphs
		A5	Visual presentation of analysis results
		A6	Support for software quality control
Lower CASE	Prototyping	P1	Quality of support for input screens
		P2	Report design features
		P3	Menu generation
		P4	Dialog flow
		P5	Ability to use sample data
		P6	Variety and quality of objects, widgets, or tool sets
	Code generation	C1	Structure of code
		C2	Support for various compilers and environments
		C3	Time to generate code
		C4	Efficiency/speed of resulting code
		C5	Size of resulting code
		C6	Ease of reading/modifying code
		C7	Size of projects supported
General	General features	F1	Variety of computers supported/multiple platforms
		F2	Network support
		F3	Compatibility with existing software
		F4	Vendor longevity and stability
		F5	Upward compatibility
		F6	Workstation configuration
		F7	Ease of customization
		F8	Size of projects it can handle
		F9	Price
		F10	Ease of installation
		F11	Quality of documentation
		F12	Internal help facilities
		F13	Vendor support (phone, BBS, etc.)

tures. This result implies that respondents perceive a difference in the actual support provided by the CASE tools. That is, tools that are strong in graphics (upper CASE) tend to be rated weaker in code generation (lower CASE).

Implications

THESE RESULTS HAVE IMPLICATIONS BOTH FOR CASE TOOL VENDORS as well as for MIS developers. Clearly, the vendors need to improve their tools. In particular, the negative relationships revealed by this study are important. They indicate that the tools are split into categories and do not provide all of the features wanted by developers. Perhaps the recent consolidation in the industry will enable the few remaining vendors to combine features and produce a product that is stronger across all of the categories.

From the perspective of developers, the results indicate that certain CASE tool features are considered to be vastly more important than others. In particular, analysis and design features such as data normalization and integrated analysis of the designs are considered more important than basic graphics features.

Within individual categories, some items are more important than others. For example, consider the leading features in each category. In graphics, ease of use appears to be the most desired property. The prototyping feature indicates that input screens and dialogs are important. In the data dictionary, the variety and quality of data saved on each item are rated highly. The analysis category stresses visual presentation of the analysis as the most important feature. In coding, structure and efficiency of the resulting code are critical. From a general-features perspective, network support, version compatibility, and customization are stronger attributes than documentation and internal help support.

Given the wide range of CASE product features, software developers will be constantly faced with choices. In the presence of competing CASE tools and the need to adapt to multiple users, these choices become more complex. As each user demands a differing mix of product features, it is difficult to evaluate the overall needs and to prioritize which features are incorporated into the next version of a CASE tool. The evaluation process described in this paper can help identify the important attributes of CASE tools and aid in the identification of features that are part of the design of complex software products.

Concluding Perspective

IS THERE A FUTURE FOR CASE TOOLS? If so, what features should the CASE tools possess? Prior research has shown mixed results for the usage of CASE tools as a whole. This new study examined the individual features of CASE tools—particularly in terms of the upper CASE and lower CASE classification.

The results indicate marked differences in the capabilities of existing CASE tools. In particular, some tools rated higher in terms of graphics and ease of use. However, the CASE tools that provided substantive analysis features were the ones that received the highest ratings. Of course, the analysis features are also correlated with graphics and data dictionary facilities, so a good CASE tool must provide adequate levels of support for these fundamental features. The main point is that users demand more than just graphics and dictionary features.

This study also revealed an important relationship between the number of CASE teams and support for data dictionary features. As the number of CASE teams increases, respondents tended to rate data dictionary features as more important. This implies that the CASE tools are being used to share data and coordinate work between project teams. Similarly, respondents working in organizations with a larger MIS staff and more employees place higher values on the coding features. Thus, CASE tools are being used for two purposes: Larger firms are emphasizing the prototyping and code-generation facilities and using them to build completed systems. Smaller firms are primarily using the CASE products for analysis and design and to share development work across teams.

This perspective appears to validate the classification process of upper and lower CASE tools which now is intertwined with organizational size. In essence, CASE tool usage and classical taxonomy are now size-dependent. This will allow for new applications and potential design modifications as the next generation of CASE tools are developed.

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