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Expertise, Task Complexity, and the Role of Intelligent Information Systems

by

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ABSTRACT

Relationships between users' expertise, task complexity of information system use, artificial intelligence, and information service mission provide the basis for a conceptual framework for considering the role that artificial intelligence might, in principle, play in information systems. Users' expertise, task complexity, and information system service mission are multi-dimensional constructs. Increasing users' expertise and/or reducing task complexity are alternatives to or complements of the use of artificial intelligence. Intelligent systems and intelligent users each need both cognitive and conceptual models. System intelligence can be assessed by the ability to discriminate reliably between different situations and is independent of whether a system is "computer-delegated" or "computer-assisted". "Computer-assisted" systems are likely to be more intelligent and more effective. Four examples of application illustrate these conclusions.

INTRODUCTION

Users of information services are faced with a variety of problems. Where information retrieval is involved there are different sets of problems: the task of accessing the system; the task of identifying and retrieving a suitable document; and the task of understanding the retrieved document. In these tasks the user is faced with difficulties associated with understanding the system used, determining what to do next, and understanding the meaning of the information supplied. Especially in the task of retrieval the user is faced with continual decisions concerning what to do, when to do it, and how to do it. The options, which may not be self-evident, are likely to be numerous, difficult to compare, unfamiliar, and/or ill-defined. We use the term "task complexity" to denote this range of difficulties. (For a general review of task complexity see Campbell (1988). For task complexity in information systems see Culnan (1984; 1985)). We use the term "expertise" to denote the user's ability to deal with this complexity.

There is a large and rapidly increasing literature on how artificial intelligence might be used to develop more "intelligent" information systems (e.g. Advances, 1985; Brooks, 1987; Brooks, Daniels, and Belkin, 1986; Davies, 1986; Florian, 1990; Gebhard, 1985; Morris and Neill, 1988; Sharma, 1987; Smith, 1987; Sparck Jones, 1983; Vickery & Brooks, 1987; Walker, 1981; Wormell, 1987). Of special interest have been "expert system" techniques using representations of experts' knowledge and rules of inference reflecting how experts apply their knowledge. The idea is to use both elements to determine automatically what course of action should be taken in any given situation. This determination might be advisory, as in computer-assisted systems, or routinely acted upon where the decision is delegated to the system.

Dreyfus and Dreyfus (1986) argue that expert systems can be expected to work effectively only in limited structured areas and that only modest levels of competence should be expected since, among humans, it is beginners, rather than experts, who follow rules.

"Expert systems" constitute a powerful tool, but, as with the powerful tools of management science, such as linear programming and queuing theory, there can be a temptation to concentrate more on applying the solution than on the nature and context of the problem.

This paper is not concerned with expert systems, at least not in any direct way, or with any of the technical aspects of implementing artificial intelligence. Rather, the intent of this discussion is to complement this empirical work by moving to a more general level and by providing a conceptual framework, in general terms, of the potential role of artificial intelligence in information systems in relation to other courses of action that can be used instead of or in conjunction with artificial intelligence. This paper (i) examines in general terms the *context* of information systems in which artificial intelligence might in principle be applied; (ii) formulates this context in terms of the relationships between (a) the expertise of the users of information systems, (b) the task complexity facing the users, (c) roles that artificial intelligence might in principle play in information systems, and (d) the purpose of the system; and (iii) suggests a framework for considering and comparing artificial intelligence in relation to other, different options in the design and use of information systems.

COPING WITH COMPLEXITY

Four courses of action are possible when the complexity of a task strains or exceeds one's expertise. We can illustrate these four options by reference to the problem of shifting gear when driving an automobile:

Option 1. Education. The user can increase his or her expertise. A novice driver could read a teach-yourself-to-drive manual.

Option 2. Advice. The system may be capable of offering helpful information. Installing a tachometer does nothing to reduce the complexity of shifting gears, but the indication of engine speed can help one judge better when and how to operate the gas pedal and the clutch. The complexity of the task is unchanged, but one is better informed.

Option 3. Simplification. If the complexity facing the user could be reduced, then the user's expertise would become more adequate *relative to* the task. The system itself could be simplified or an interface, either a human intermediary or an artificial "front-end," could make the task *simpler for the user* even though the system itself may remain just as complex. The novice driver could stop driving, hire a chauffeur, use only the lowest gear, or change to an electric motor that has only one gear.

Option 4. Delegation. The *user's* role in coping with complexity would be eased and any given level of user expertise would become more adequate relative to the system if some of the complexity could be *moved inside* the system and away from the user. Automatic transmission makes the task of shifting gears much easier for the driver. The complexity of shifting gears is still present, but the burden of dealing with it has been removed from the (human) driver to the (artificial) automatic transmission system. Insofar as artificial intelligence is viewed as "the science of making machines do things that would require intelligence if done by men" (Minsky, 1963, p. 406), an automobile automatic transmission is a well-known and successful example of artificial intelligence.

These four approaches to the need for the user's expertise being sufficient for the complexity of the task can be sorted in two ways:

(a) They vary in approach. Two of them (1 & 2) are concerned with *improving the user's expertise*, i.e. the user's ability to cope with complexity. The other two (3 & 4) seek to *reduce the user's need to cope with complexity*, i.e. to make the user's existing expertise more adequate relative to the task.

(b) They vary with respect to the locus of the solution. In two cases (1 & 3) the change is introduced from the environment in the form of more education for the user (1) or simplification of the system (3). In both cases the role of the system is a passive one. In the other two cases the system adopts an active role, either by providing helpful information to the user (2) or by itself taking responsibility for dealing with some of the task complexity. Locus depends on where the system boundaries are drawn. For example, by definition, we regard an intermediary (chauffeur) as being outside the information *system* even though part of an information *service*.

These patterns can be shown as a two-by-two contingency table. See Table. 1.

	INCREASE EXPERTISE	REDUCE THE NEED FOR EXPERTISE
CHANGE FROM ENVIRONMENT	1. User education	3. Simplify task. Use intermediary.
CHANGE FROM WITHIN SYSTEM	2. Make the system offer advice	4. Delegate tasks to the system

TABLE 1. Different tactics for task complexity.

Because the feasibility and cost-effectiveness of adopting each of these four tactics is likely to vary greatly from one situation to another, selecting a cost-effective solution depends on careful comparison of these quite different strategies.

VARIETIES OF TASK COMPLEXITY

In this discussion we are simply using the term complexity to denote whatever difficulties the user may face, but in reality there are distinct types of difficulty or dimensions of complexity (Campbell, 1988). In considering use of an information retrieval system a distinction can be made between difficulties arising from the subject matter of the inquiry and those arising from the retrieval system itself (Culnan, 1984; 1985).

Ingwersen (1984) proposed four categories of user of online bibliographic retrieval system:

i. The “elite”, who have both expertise in using the information retrieval system and good knowledge of the subject area;

ii. The “intermediary”, who has expertise in using the system but lacks appropriate subject expertise;

iii. The “end-user”, who has expertise in the subject but not in the system; and

iv. The “layman”, who has expertise in neither the system nor the subject matter.

One can argue that intermediaries and end-users are not necessarily lacking in subject expertise and system expertise respectively. Further, the elite are, by definition, end-users and the ideal intermediary would be a member of the elite. But this is mere quibbling over the labels.

Ingwersen's four categories can also be expressed as the four possible combinations of high and low values for each of the two dimensions of (a) expertise in using the retrieval system, and (b) expertise in the subject area of the inquiry. This is clearly a simplification. Treating each of the two kinds of expertise as a continuous scale would provide a more generalized version of this categorization. In effect one would represent each user's expertise as a point in two dimensional space, as shown in Figure 1, where Ingwersen's four categories are indicated. A person with medium competence in using the system and a medium knowledge of the subject area would be positioned in the middle.

```
                          SYSTEMS EXPERTISE

               HIGH                        LOW
          HIGH +))))))))))))))))))))))))))))), HIGH
               * Elite             End-user *
               *                ^           *
               *               A*           *
 SUBJECT       *        B       *           *
               *     <)))))) Medium         *
EXPERTISE      *                            *
               *                            *
               *                            *
           LOW * Intermediary        Layman * LOW
               .))))))))))))))))))))))))))))-
               HIGH                       LOW
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FIGURE 1. Expertise as a two-dimensional space.

Increasing the user's subject expertise would move the user's position in this space upwards along the arrow marked A. Increasing the user's expertise with the system would move the user's position to the left along the arrow marked B. The ideal might seem to be always in the top left hand corner, but this is unlikely, expensive in effort, and generally unnecessary. One's position in such a space would vary from system to system and from one inquiry to another, depending on the subject concerned. Inquiries and systems vary in the amount of complexity involved and, therefore, in the expertise required.

The expert's paradox is that greater expertise both increases and decreases information-seeking success. The greater the expertise the greater the probability of finding any information (i.e. pertinent material) and the lower the probability that it would be informative (i.e. novel to the searcher) (Christozov, 1990).

This discussion has been stated in very general terms. Ingwersen's four categories based on two dimensions may well come to be replaced by more complex categorizations as a result of further research, but they do provide a basis for an initial conceptual framework. However, the conceptual framework developed thus far has an inherent limitation: It might be useful as a basis for improved performance (efficiency or cost-effectiveness), but it cannot be used for the *evaluation* (cost-benefit analysis) of any given design except in relation to the purpose of the information service of which the information system is a part. The role and mission of any given information service are necessarily unique and situational (Buckland, 1989). The preference with respect to outcomes, the basis for evaluation, is also, in practice, complex and multi-dimensional (e.g. McDonald, 1987).

Whatever assumptions are made in any given example concerning criteria for evaluation, the conceptual structure outlined above provides a framework for the systematic identification of options and trade-offs. e.g. (a) The effectiveness of increasing subject expertise (moving upwards) compared with greater systems expertise (moving left). (b) The feasibility of increasing the user's subject expertise (i.e. to move a user upwards) and/or of increasing the user's systems expertise (i.e. a move to the left). (c) The most cost-effective ways of increasing expertise in either direction. The answers to (a)-(c) are likely to vary by field of discourse, by type of inquiry, and by user. They are likely to vary by type of information system or interface. What are the implications of the desirability of increasing each type of expertise for the design of information systems and especially their interfaces? The less user-friendly the system, the greater the need for the user to be a subject expert and, more especially, to be expert with the system. The more user-friendly the system, the less the need. Hence the increased effectiveness in use resulting from moving the user to the left in this two-dimensional "expertise-space" could be seen as an empirical indicator of user-friendliness.

To what extent and at what cost could the user's need for expertise to deal with the complexity of the system be reduced? How far can the task complexity facing the user be reduced by lessening the complexity and/or by moving it away from the user into the system? How costly are the deleterious consequences of any given level of task complexity?

A variety of improvements can readily be imagined. The real challenge is not simply to develop more intelligent information systems any more than it is to develop more intelligent users of information systems or to make systems that are less difficult to use. All three approaches are desirable, but the real challenge is to determine the best combination of these strategies.

Language

We have used a two-dimensional model of expertise for simplicity. Reality is more complicated. In particular, difficulties caused by language barriers need to be included. Even distinguished subject experts learn little from material in foreign languages they do not understand and even skilled searchers encounter difficulties when interfaces, "help" screens, and system documentation are in an unfamiliar foreign language. Adding language as an additional dimension of expertise yields a three dimensional "expertise space". The language barrier is commonly ignored in English language literature on the design and evaluation of information systems, but theories and research concerning information systems that do not include language barriers are necessarily incomplete.

Consider, for example, the language problem faced by a German-speaking user trying to use an English-language interface. A number of quite different solutions are possible:

(a) Increase the user's language expertise: Get the user to become fluent in English as well as German;
(b) Build advice into the interface by providing, online, English-German and German-English dictionaries;
(c) Make the task easier for the user by simplification, substituting a German-language based system, or

by providing aid for dealing with the system, e.g. by providing a bilingual intermediary or front-end. (In this paper we do not discuss intelligent front-ends, regarding them as being, like human intermediaries, outside the information system by definition. However, the same sort of considerations apply to intelligent front-ends as to intelligent information systems).

(d) Moving complexity from the user to the system by making the system's interface capable of handling natural language and bilingual.

The relative cost-effectiveness of these courses of action would depend on the circumstances. Making the system itself bilingual would be inefficient for one non-English-speaking user, but would probably be the most cost-effective solution if there were many.

TACTICS AND EXAMPLES

We now examine more closely the types of tactics that might be adopted in the use of artificial intelligence in information systems, while noting that to *evaluate* possible uses of artificial intelligence in providing information systems it is necessary also to consider alternative solutions *outside* of the system, such as an increase in the user's education (category 1 above) and simplifying or mediating the system (3). The tactics that involve the use of artificial intelligence in an information system fall into the two active categories (2 & 4) noted above.

Tactics of advice: Improving the user's expertise. This class of tactic seeks to increase the user's understanding of the system and of how it works, so that the user can know better what the options are and how the systems works. In large measure this can be viewed as "revealing the structure." This approach has been referred to as developing the user's "conceptual model" of the system (e.g. Duncan & McAleese, 1987).

Tactics of delegation: Reducing the user's need for expertise by moving responsibility for coping with task complexity into the system. To the extent that the system itself can predict reliably what the user wants done, tasks and their associated complexity can be delegated to the information system itself. This reduction in the task complexity facing the user constitutes a reduction in the user's need for expertise. But this delegation depends critically on the system's ability to predict what the user wants done. The system has to know -- or be able to learn -- about users' (changing) needs and preferences. In other words, the system needs to have a "cognitive model" of the user, preferably an adaptive model.

The more the system can assume about the user, the more reliably it can assume what the best next step should be. This is reflected in interfaces that default to what is inferred to be the preferred next step. This is true whether the system tactics of advice or tactics of delegation are attempted.

The difference between the two tactics can be illustrated by a hypothetical example:

Example 1: A difficult text. Suppose that, in an information system that can retrieve texts, a text is retrieved that the user finds difficult to understand. This problem, common in library use, although neglected in the literature, is likely to occur when someone asks a technical question, the answer to which is outside the user's area of expertise. With considerable simplification the situation can be represented symbolically in terms of the relationships between two scales: (i) The difficulty (complexity) of the text; and (ii) The expertise (knowledge) of the user. Doubtless these are complex multi-dimensional domains in reality, but this mismatch is represented symbolically as if one-dimensional in Figure 2 for the sake of explanation.

```
                           ----------->
DIFFICULTY       Very ))))) D ))))))))) F ))))))) Not
 OF TEXT       difficult    :          :       difficult
                            :          :
                            :          :
EXPERTISE        Very ))))) E ))))))))) C ))))))) Not
 OF USER        expert       <-----------          expert
```

FIGURE 2. User's Expertise (C) and Difficulty of a Text (D).

What needs to happen for this mismatch to be resolved? Solutions from outside the system include persuading the user to acquire more education (option 1., defined above) or to change to some other simpler text (option 3). For the information system to be effective (i.e. for the user to become informed), using solutions internal to the information system, those in which the system plays an active role require some combination of the tactics of advice (option 2) and of delegation (option 4). Tactics of advice would lead to a move in the position of the user from C towards E where it would correspond to D. Relevant techniques could include online access to general and specialized dictionaries, encyclopedias, grammars, textbooks, etc., as needed to supply the additional background knowledge. This improvement in the user's expertise is indicated symbolically by the difference between C, denoting the prior state of knowledge, and E, denoting a state of knowledge matching the difficulty of the text. The distance from C to E denotes the increase in the user's expertise.

Tactics of delegation would be concerned not with increasing the user's expertise but with reducing the difficulty of the text, interpreting or translating the difficult text (D) into a less difficult text (F) suited to the user's level of expertise. In this case, however, there is an important constraint. Attractive though a simplified text might be, simplification necessarily involves some loss of information and it is also necessary for the complexity of the text to remain sufficient to answer whatever the original inquiry may have been.

In imagining examples of this problem, it rapidly becomes clear that not all cases would be the same. Consider the difference between (i) an English-speaking user who finds the concepts and vocabulary difficult to understand even though the text is in English; (ii) an English-speaking user that has difficulty with the text because it is in German; and (iii) a German-speaking user that understands the concepts but has difficulty because the text is in English. These three cases call for quite different sorts of interpretation: Complex English to less complex English for (i); machine translation from German to English for (ii); and machine translation from English to German, or possibly into simpler English, for (iii). Selection of the appropriate course of action, would require the system to make (or be told) the correct assumption concerning the user. The sum of the system's assumptions concerning the user has been called the (system's) "cognitive model" (Duncan & McAleese, 1987).

Cognitive models and conceptual models.

The custom of using "conceptual model" to denote the user's assumptions concerning the system and "cognitive model" to denote the system's assumptions concerning the user has disadvantages. The meanings of the two terms are not obvious or self-explanatory. Insofar as "conceptual" ordinarily relates to understanding and "cognitive" ordinarily relates to learning, the usage is not entirely correct. For an intelligent system to be effective it needs to be able to make assumptions not only about what the user knows but also about how the user learns. Non-trivial knowledge of a system on the part of a user includes assumptions about how the system adapts to (i.e. infers from) different situations. In effect, the system's assumptions about the user and the user's assumptions about the system *both* contain conceptual *as well as* cognitive elements (*cf* Hollnagel, 1987).

The two sorts of tactics noted above can be further illustrated by another example:

Example 2: Initial search command in information retrieval. Information retrieval depends on the matching of the representation of an inquiry (i.e. the search command) and the representation of what is retrievable in the system (Belkin & Croft, 1987). Various problems arise in the matching, e.g. with homographs (e.g. LAFAYETTE, California; LAFAYETTE, Indiana; LAFAYETTE, Marquis de; etc.) and with synonyms and different-but-related terms (e.g. AI; ARTIFICIAL INTELLIGENCE; EXPERT SYSTEM; INTELLIGENT INTERFACE).

Tactics of advice include revealing the structure, enabling the user to examine and become familiar with the indexing terms used and with their interrelationships. With tactics of delegation, the system would make inferences about what the user wanted retrieved and act accordingly. Synonyms and related terms would be invoked automatically and homographs (e.g. places named for the Marquis de Lafayette) would be selectively discarded on the basis of the inferences that the system draws from its assumptions concerning the user.

However, as one begins to explore actual or hypothetical cases, the difference between these two tactics tends to become increasingly blurred. Tactic one ("revealing the structure") has two components:
(i) The first component is the capability of revealing the structure, e.g. segments of indexes and useful "help" screens. Every system is programmed to have more or less of this capability, but even copious provision of this capability does not in itself imply the provision of an intelligent system. The revealing of the structure could be very extensive, but entirely passive, available only as invoked by the user. Such a situation does not require any of the knowledge bases or rules of inference characteristic of an expert system.
(ii) The other component is knowing *when* to reveal which part of the structure. A system would become intelligent when the revealing of the structure is programmed to be situational, i.e. the system itself infers what particular part of the system would most usefully be revealed and decides when, without being intentionally invoked by the user, to supply information likely to be helpful concerning the system. In other words the system decides when and how to try to improve the user's understanding of the system. Unprompted, situational "help" screens are a good example. The more intelligent the system the more different situations it can identify as a basis for selecting a part of the system to reveal.

A proactively helpful system is one that presumes to propose or perform what it infers needs to be done next. However, the degree of "intelligence" involved can vary greatly. A relatively unintelligent system might, in any situation determined to be problematic (e.g. retrieval of zero or an excessive number of items) return the user to an initial menu to start again. A more intelligent system would draw inferences from the situation to select which next action to perform or to propose. Computer Assisted Instruction systems vary greatly from simple menus to promptings based in conclusions drawn from the user's input. The more different situations a system can distinguish as the basis for selecting some alternative next action, the more intelligent we should be inclined to consider it to be.

A PRAGMATIC MEASURE OF SYSTEM INTELLIGENCE

In both the tactics of advising and the tactics of delegation, the intelligence of the system lies in its ability to discriminate between a variety of situations in order to determine what action would be appropriate. The ability to choose outcomes situationally can be illustrated by imagining an information system that died whenever it encountered an unusual situation. A system that returned the user to the main menu to start again whenever an unusual situation was encountered would be more user-friendly but could hardly be described as helpful or intelligent.

This formulation suggests that the intelligence of a system could be indicated pragmatically by the number of different, situation-related responses it can reliably provide. On this basis, when comparing expert systems in any given situation, the system that can identify the most different situations with any given level of reliability would be regarded as the more intelligent and for any given number of recognized situations the system that discriminated most reliably would be the most intelligent. Two conclusions follow from this view of system intelligence:

(i) It is not at all clear that a system following the tactics of advice is inherently any less intelligent than a system using tactics of delegation, programmed to determine the next step to be taken. Rather, both sorts of systems could be more or less intelligent.

(ii) Intelligence, in this context, has to do with the diagnosing and drawing of inferences from assumptions and situations. In the case of information systems, assumptions and situations have two components: (a) The characteristics of the system, including the database; and (b) The need and expertise of the user. Unless the user, for whom the system has been developed, is to be ignored, diagnosis of the situation depends, both for the system and for the user, on the ability to judge both the system's situation and the user's. This is particularly relevant when the searching has been delegated by the end-user to an intermediary.

"COMPUTER-ASSISTED" AND "COMPUTER-DELEGATED"

It is tempting to assume that the truly intelligent systems are those in which decision-making has been delegated to the computer and that "computer-assisted" systems, those using tactics of advice, are either not intelligent or in some sense less intelligent. These assumptions are erroneous as two following examples show.

Example 3: Record consolidation. A noteworthy example of a successful application of artificial intelligence in libraries is the use of automated procedures to compare similar bibliographic records in order to decide which pairs of records are (a) records that are variant descriptions of the same edition and so should be merged ("consolidated") and (b) records that, although similar, relate to different editions and so should *not* be merged. Erroneous merging has more serious consequences than failing to merge. Decision rules operating on weighted comparison of several different attributes of records have been in operational use for some years (e.g. Coyle & Gallagher-Brown, 1985). Not only does such a system infer which records should be merged, but, in practice, on grounds of economy, the inferences of the system are accepted as decisions without individual review by expert catalogers.

It is reasonable to assume that performance would be improved, in terms of the proportion of decisions made correctly, if the system's inferences, or at least some of them, *were* reviewed by human experts. Suppose that the arrangements were changed so that each of the system's inferences were to be reviewed by a human expert. The situation would then have changed from a "computed-delegated" expert system to a "computer-assisted" expert system, but the change has involved no change in the expert system itself, only in the subsequent use of its inferences. The system has not been made any less intelligent by being changed from "computer-delegated" to "computer-assisted." This point can be further illustrated by:

Example 4: Excessive retrieval. A problem with online bibliographic retrieval systems is that searches commonly yield an excessive number of retrieved items. The continued growth in the size of bibliographic databases exacerbates this problem. In the larger databases it is not uncommon for a search command to retrieve thousands of items when one or a few are all that are wanted.

This problem can be addressed by modifying the search command in a variety of ways, e.g. redefining the topic of the search more narrowly, limiting the retrieved set to English language material, or excluding older references, in order to obtain a retrieved set of an acceptable size. Applying weightings and assumptions to the search statement can define a gradation of progressively smaller retrieved sets to yield whatever size is preferred, in an extreme case a strict ranking.

Each combination of search command modifications would yield a different subset of a different size (or a different ranking) with different characteristics for any given initial search in any given database at any given point in time. The particular subset and, therefore, the combination of search command modifications to be preferred depends on the goals of the user on that occasion. The best subset for a multi-lingual searcher pressed for time is unlikely to be also the best subset for a patient mono-lingual searcher wanting the latest material whether immediately available or not. Choosing the optimal search modification, then, is situational both with respect to the characteristics of the data set initially retrieved and to the user's preferences at that moment. An intelligent system could analyze the subset initially retrieved, calculate the effects of various search modifications, and, making assumptions about the user's preferences, select a modification to the search, and present the resulting subset. Alternatively the system could be set to default differently. It could, as before, analyze the initially retrieved set, examine the alternatives, then, on the basis of assumptions concerning the user, merely propose one or more search modifications as likely to be optimal for the user to select, revise, or reject.

The differences between these two options are (a) the difference between a computer-delegated and a computer-assisted search modification and (b) how the default is set to perform or merely propose what should be performed. It cannot be said that either is a more intelligent system than the other. We conclude from examples 3 and 4 that although a computer-delegated system implies some degree of system intelligence, the degree of system intelligence is independent of the degree of delegation. In other words the distinction between “computer-assisted” and “computer-delegated” should not be confused with differences in system intelligence. Alternatively, other things being equal, “computer-assisted” systems involve more total intelligence because the user’s expertise is invoked in addition.

THE USER’S PERSPECTIVE

For system designers the prospect of building intelligent systems to which decisions can be delegated is an attractive challenge. For the user the perspective is less simple. As in example 3, a preference for computer-delegated over computer-assisted systems may be a matter of economy rather than effectiveness. Administrators may well prefer “delegated” over “assisted” solutions in order to reduce labor costs so long as the penalties for error do not outweigh the labor savings.

Unless one presumes the user to be dangerously lacking in expertise, it is inherently unlikely that adding the expertise of the user to the expertise of an intelligent system would not increase the quality of the outcome.

Three considerations argue in favor of computer-assisted over computer-delegated systems:

(i) As a general principle, the one thing better than being able to delegate, is not needing to delegate. Likewise the one thing better than receiving advice is not needing advice. The first consideration argues in favor of advice rather than delegation. The second argues for improving the user’s expertise in order to diminish the need for any kind of help.

(ii) An intelligent system that tried to outguess the user as to what is needed and how the user might behave (as in probabilistic retrieval systems (e.g. Bookstein, 1984)) would seem to work best with a user who is static rather than capable of learning and adapting. A user with intelligence can be expected to adapt to the system and to try to predict the system’s future actions. At least in theory, a highly adaptive system and a highly adaptive user could combine to create a situation so dynamic as to be frustrating and even unstable (“hunting”). Dynamic user behavior would argue for computer-assisted rather than computer-delegated processes.

(iii) Delegation, with computers as with people, invites the possibilities of undesirable decisions by the person or machine to whom the decision has been delegated. The more that decisions are subject to verification and approval, the more reliable the decisions are likely to be and the more the relationship changes from delegation to advisory. A patient in a hospital would presumably prefer intelligent medical systems to be no more than advisory to the doctors.

COMPARATIVE COST-EFFECTIVENESS

As was noted above there is considerable variation in the feasibility and cost-effectiveness of different courses of action. The feasibility is partly a matter of technology and partly a matter of authority. Consider for example the problem of using a U.S. online service with an English language command language in a German-speaking country. International bodies could define and promote a common command language. The U.S. host could provide a German language or bilingual interface. The local information center might be able to develop a German language front-end or provide a bilingual intermediary. The user might learn English. Feasibility varies with the position of the stake-holder. Technological improvements and enabling research continuously reduce constraints on what is technically feasible. Further, system simplification through the adoption of standards can reduce the complexity for large numbers of people very economically. These different courses of action are interrelated. For example, for the user of multiple online bibliographic systems complexity and, therefore, the need for expertise would be reduced by the general adoption of a common command language or of a linked systems protocol (Buckland & Lynch, 1988). The former would reduce complexity; the latter would move it inside the system. In addition, moving towards a common command language (and common telecommunications standards) should reduce both the need for and the probable cost of implementing linked system protocols.

SUMMARY

Exploration of the relationships between user expertise, task complexity, and the scope for the use of artificial intelligence leads to the following conclusions:

1. The expertise of the user needs to match the task complexity. When expertise is insufficient, two sorts of solution derived from the environment may be possible: Increasing the user's expertise through education; and simplifying the system. Also two sorts of solution can be built into the system using "intelligent" techniques: "Tactics of advice" and moving some of the complexity inside the system ("tactics of delegation").

2. The feasibility and cost-effectiveness of different solutions are likely to vary greatly according to the circumstances.

3. A pragmatic measure of a system's intelligence is the number of situation-related outcomes the system can reliably distinguish. On this basis, in any given context, other things being equal, system intelligence can be assessed by two criteria: the number of different situations the system can identify and the reliability with which they are identified.

4. The distinction between "computer-delegated" and "computer-assisted" systems is logically separate from the intelligence of the systems.

5. A computer-delegated system may be more economical than a comparable computer-assisted one, but, unless the expertise of the users is assumed to be so low as to be a liability, for all levels of system intelligence a computer-assisted approach is likely to be more effective because the intelligence of the system and the intelligence of the user ought to augment each other.

6. The distinction between the assumptions made by the system concerning the user and the user's

assumptions concerning the system are both important. Calling the former a "cognitive model" and the latter a "conceptual model" is potentially misleading. Insofar as a "conceptual" denotes knowledge and "cognitive" denotes learning, both the system's model of the user and the user's model of the system, if well developed, will include both conceptual and cognitive elements.

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