Knowledge Matters: Performance with Decision Support

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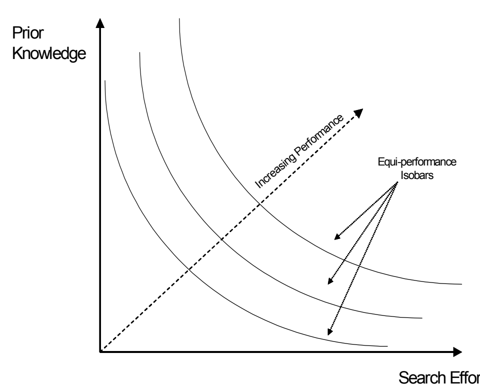
Background and Research Question. There has been a long tradition of experimental research exploring the behavioral aspects of effective decision support; from the well-known Minnesota experiments (Dickson, Senn et al. 1977) to the more recent series of studies by Todd and Benbasat (Todd & Benbasat 1992; Todd & Benbasat 1993; Todd & Benbasat 1994; Benbasat & Todd 1996; Todd & Benbasat 1999). Yet despite the volume of research, rather surprisingly, user domain knowledge has not been commonly featured explicitly as a central construct. In this study, we address the question of the effect of knowledge on performance with a decision tool in a preferential choice task.

That user domain knowledge is important, even in a preferential choice task such as a consumer purchase decision, seems axiomatic. The nature of the effect of user domain knowledge is, however, very much an empirical question. For example, knowledge can be very helpful, improving the problem solving performance obtained for a given level of effort (Newell 1990), even without decision support. Alternatively, the domain knowledgeable user may be less mindful (Langer 1989), or more complacent and thereby fail to take full advantage of the functionality offered by the decision tool. The purpose of this study is to empirically explore the potentially divergent effects of knowledge. Specifically, this research asks the question: what is the effect of domain knowledge on performance with a decision tool in a preferential choice task? Drawing on prior work, we consider the influence of domain knowledge and effort on accuracy with two different decision tools varying in effort and knowledge requirements.

Theory and Hypotheses. In a preferential choice task, a range of decision strategies of varying degrees of effort and accuracy have been observed and described in the behavioral decision theory literature. Decision makers recognize the trade-offs between effort and accuracy and select an appropriate strategy as an adaptive response to the goals and constraints they face (e.g., incentives for accuracy versus limited available time for strategy execution) (Payne et al. 1993, Johnson & Payne 1985). Extending the Effort-Accuracy research, Todd and Benbasat found that decision tools can add value by decreasing effort, given a desired level of accuracy (Todd and Benbasat 1992) or increasing the accuracy achieved given a certain level of effort (Todd and Benbasat 1999). The twin objectives, accuracy maximization and effort minimization, generate value to a user as he or she makes trade-offs with a decision support tool, although effort minimization tends to take precedence over accuracy maximization (Todd and Benbasat 1994; Benbasat and Todd 1996). The most important goal for decision support tools in this context is to reduce the effort required to execute a given strategy and thus make a more accurate strategy available for less effort, thereby improving performance.

The Effort-Accuracy literature does not directly consider the role of domain knowledge. In the preferential choice task context, knowledge may include knowledge of attribute ranges, attribute trade-offs (of value in a compensatory strategy) or of which attribute best facilitates distinguishing between different alternatives (which could assist in compensatory strategies or in non-compensatory strategies, such as the lexicographic strategy). Knowledge may also be in the form of a specification of a stereotypical ideal (Fiske and Pavelchak 1986). Knowledge can substitute for effort (Newell 1990). Thus, any consideration of knowledge effects is potentially confounded if it does not also consider effort effects. Similarly, any study of effort is potentially confounded if it does not consider or appropriately control for knowledge. Knowledge and effort also complement each other; performance is enhanced when a decision maker relies on a combination of effort and knowledge rather than exclusively on one factor alone.



As substitutes, a decision maker can compensate for a lack of knowledge with additional effort and still achieve a given level of performance. Conversely, a knowledgeable decision maker can achieve a given level of performance with less effort than a less knowledgeable individual. Newell (1990) elegantly characterizes this as a trade-off between prior knowledge and search effort in terms of "equi-performance isobars" (see figure adapted from Newell 1990). How does this effort-knowledge relationship come into play in the presence of decision support? Clearly, tools will vary with respect to the effort required, the accuracy they can achieve, and the requirement and opportunity for exploiting knowledge. As a control, we developed a tool (LEX) which facilitates a lexicographic strategy that is non-compensatory, low effort, low accuracy, and low in knowledge requirements and opportunities. We contrast this with a parametric search tool (PS) that facilitates a more compensatory strategy and consequently is potentially high in accuracy, high in knowledge requirements and opportunities and offering greater potential returns on effort. We do not make hypotheses for LEX, as LEX users are our control group; we expect little effect with LEX for knowledge or effort per principle P4 below.

In formulating our hypotheses (H1-H6), we build on several principles (P1-P5) developed from the theory:

P1: Knowledge and effort both can contribute to performance. As potential substitutes, they must be examined together rather than in isolation.

P2: Tools imply decision strategies (LEX: the non-compensatory Lexicographic strategy; PS: a partially compensatory strategy).

P3: Given the effort minimization evidenced in prior research, users will adopt the strategy implied by the tool.

P4: Effective use of LEX requires low effort and low knowledge, thus providing little opportunity for exploiting either for performance improvements, since it does not facilitate a compensatory strategy.

P5: Effective use of PS requires high knowledge or effort, thus providing substantial opportunities for exploiting either for performance improvements, since it facilitates more of a compensatory strategy.

H1: *Users who exert higher effort will achieve higher accuracy with the PS tool for a given level of knowledge.* This is consistent with prior effort-accuracy research, while controlling for any effort-knowledge substitution.

H2: *For a given level of knowledge, effort will have a greater effect on accuracy for users of the PS tool than for users of the LEX tool.* Since PS facilitates a compensatory strategy, it offers greater opportunity for performance improvement through greater effort (per principles 4 and 5).

H3: *Users with higher knowledge will achieve higher accuracy with the PS tool, for a given level of effort.* The user is able to reach a higher equi-performance isobar through higher knowledge for a given level of effort.

H4: *For a given level of knowledge, higher knowledge will have a greater effect on accuracy for users of the PS tool than for the users of the LEX tool.* As with effort in H2, given that PS partially facilitates a compensatory strategy, it offers a greater opportunity to leverage knowledge for performance gain (per principles 4 and 5).

H5: *The interaction of knowledge and effort will positively affect accuracy for users of the PS tool.* Knowledge and effort together offer synergistic gains in accuracy: the equi-performance isobars are convex.

H6: *The effect of the interaction of knowledge and effort on accuracy will be greater for users of the PS tool than for users of the LEX tool:* a natural extension of the arguments for H2, H4 and H5.

Research Design. Using a purpose-built web shopping simulation, we studied 56 subjects interacting with two different decision tools in the purchase of a printer (a training task) and a computer (the experimental task). In each case we constructed a product database (of more than 200 unbranded items) that was preference indifferent (i.e., not skewed in favor of any particular attribute), consistent with current market offerings and with slightly more than twice the number of dominant products as there were attributes. This is consistent with the design of Haubl and Trifts (2000) using a product space with a small, but non-trivial number of dominant products.

We operationalized accuracy using a novel application of Data Envelopment Analysis (DEA) (Charnes et al. 1978; Banker et al. 1984). DEA permits the calculation of an "efficient frontier" representing a preference indifferent range of optimal combinations of different attributes. Accuracy was measured as the distance between a subject's chosen product and the DEA frontier. Following Fischer et al (1999) and Haubl and Trifts (2000) we operationalized effort in terms of decision time taken. We operationalized knowledge using the well-established self-assessed subjective measure of product category knowledge (Sujan 1985). We employed a between-subjects design manipulating the decision tool provided to the subjects, with roughly half receiving LEX and half receiving PS. Effort was measured but not manipulated other than uniformly making it salient through a reward scheme. We relied on randomization to ensure even distribution of knowledge across treatments.

Conclusion. We find that effort positively influences accuracy, with a greater effect observed for the more powerful decision tool, PS. In conflict with theory and intuition, we find knowledge has a negative effect on accuracy, and that this effect is greater with the more powerful decision tool. We interpret our results in terms of knowledge-effort substitution, the content and representation of knowledge, and the conceptual characteristics of the decision tool. More specifically, if knowledge is in the form of a stereotypical ideal (Fiske and Pavelchak 1986), knowledgeable users may have searched for a match to their ideal. Such a search could be relatively lengthy (since there maybe fewer matches to this stereotypical ideal than there are dominant products in the database) and suboptimal (as the subject's ideal may be dominated in our particular product set). Our results emphasize the importance and complexity of knowledge considerations in understanding performance in decision support. Pragmatically, it highlights how user knowledge may both constrain and enable effective performance with decision support systems.