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The Impact of Task Complexity—Decision Aid Fit on Decision Quality in Business-to-Consumer Electronic Commerce

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Keywords: Individual Decision Making, Heuristic Decision Rules, DECISION AIDS, Optimization Methods, ONLINE IS, Information Search and Retrieval, MARKETING IS, Human/Computer Interaction

Primary Research Area: Optimization of Individual Decision Making

Research Problem

In Business-to-Consumer (B2C) electronic commerce, the conversion rate of lookers-to-buyers averages 2%, 2 buyers for every 100 lookers. We believe that this rate is due, in part, to decision aids that do not fit task complexity. The model developed in this research could have direct implications for electronic commerce enterprises that are trying to increase their conversion rates. Web stores could dynamically detect the current task complexity and either recommend or impose a particular decision aid. A dynamic detection could be tailored to the individual's customer profile or real-time behavior.

Figure 1.

Literature Review, Theory Base, and Model Development

We draw from several literatures: Economics of Search, Utility Theory, Behavioral Decision Theory, and Consumer Decision Making. We also develop a typology of ten real-world Product Search Engines (PSEs), analyzing them in terms of constructs from the literatures. We analyze one of the best PSEs (www.personalogic.com) with a linear optimization technique, Data Envelopment Analysis (DEA), and show that the recommended products are far from optimal.

The model consists of three stages, each having a different task complexity. In order to measure decision making quality, we apply DEA to identify choices of products that dominate other products on the basis of attribute values.

Figure 1 is our three-stage decision making model:
Based on both the literature and real-world PSEs, Figure 2 is our hypothesized combination of factors that represent Task Complexity–Decision Aid (TC–DA) fit:

<table>
<thead>
<tr>
<th>Maximum Number of Attributes</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Number of Products</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Weighted Additive (WADD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elimination By Aspects (EBA)</td>
<td></td>
<td></td>
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<tr>
<td>Elimination By Aspects (EBA)</td>
<td></td>
<td></td>
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<tr>
<td>Parametric Search (PS)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Low-Low TC would be best fit by WADD, the standard matrix of Products by Attributes. High-High TC would be best fit by PS, commonly found in PSEs. Intermediate TC would be best fit by an intermediate decision aid, such as EBA.

**Hypotheses**

We will test two sets of hypotheses that hinge on the information retrieval concepts of recall and precision. Recall is the proportion of current relevant products relative to the previous set of relevant products. Precision is the proportion of current relevant products relative to the current irrelevant products. Relevant is equivalent to optimal or efficient in a DEA sense. Current refers to the set of products at the current stage of decision making: search, consideration, or choice. Efficiency at the different stages refers to the average DEA efficiency of the current set of products.

The first set of hypotheses relates the above constructs to TC–DA fit.

H1a) Search recall will be higher with TC–DA fit than without it.

H1b) Search precision will be higher with TC–DA fit than without it.

H1c) Search efficiency will be higher with TC–DA fit than without it.

H2a) Consideration recall will be higher with TC–DA fit than without it.

H2b) Consideration precision will be higher with TC–DA fit than without it.

H2c) Consideration efficiency will be higher with TC–DA fit than without it.

H3) Choice efficiency will be higher with TC–DA fit than without it.

H4) Product purchase likelihood will be higher with TC–DA fit than without it.

The second set of hypotheses deals with the likelihood of purchase increasing as a result of improved decision outcome efficiencies.

H5a) The higher (lower) the search recall, the higher (lower) the product purchase likelihood.

H5b) The higher (lower) the search precision, the higher (lower) the product purchase likelihood.

H5c) The higher (lower) the search efficiency, the higher (lower) the product purchase likelihood.

H6a) The higher (lower) the consideration recall, the higher (lower) the product purchase likelihood.

H6b) The higher (lower) the consideration precision, the higher (lower) the product purchase likelihood.

H6c) The higher (lower) the consideration efficiency, the higher (lower) the product purchase likelihood.

H7) The higher (lower) the choice efficiency, the higher (lower) the product purchase likelihood.

**Methodology**

We choose to use an experiment to maximize internal validity. We will implement a web store as realistically as possible to maximize external validity. The experimental design is a 2x2x2x2 factorial design of the following dimensions:

- Maximum number of attributes: low or high
- Starting number of products: low or high
- Search aid: parametric search (PS) or no support
- Consideration aid: elimination by aspects (EBA) or no support

We may compactly represent this experimental design as in Figure 3:
Figure 3.

<table>
<thead>
<tr>
<th>Starting Number of Products</th>
<th>Maximum Number of Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>WADD</td>
</tr>
<tr>
<td>S1: PS or Not</td>
<td>S1: PS or Not</td>
</tr>
<tr>
<td>S2: EBA or Not</td>
<td>S2: EBA or Not</td>
</tr>
<tr>
<td>S3: WADD</td>
<td>S3: WADD</td>
</tr>
<tr>
<td>High</td>
<td></td>
</tr>
<tr>
<td>S1: PS or Not</td>
<td>S1: PS or Not</td>
</tr>
<tr>
<td>S2: EBA or Not</td>
<td>S2: EBA or Not</td>
</tr>
<tr>
<td>S3: WADD</td>
<td>S3: WADD</td>
</tr>
</tbody>
</table>

Legend
S1: Search Stage
S2: Consideration Stage
S3: Choice Stage

Summary

The contributions of the proposed research are five-fold. We will
1. combine the classic literature on decision strategies with the emerging literature of e-commerce,
2. show that decision aids should match task complexity to increase decision quality and purchase likelihood,
3. introduce DEA for measuring the quality (optimality) of decision making,
4. use search, consideration, and choice metrics to gauge decision quality, and
5. suggest to e-commerce retailers that they improve their conversion rates by redesigning their decision aids to increase decision outcomes. This could be done by detecting the current task complexity and either recommending or imposing a particular decision aid tailored to the individual's customer profile or real-time behavior.

References


