2D versus 3D Visualizations in Decision Support – The Impact of Decision Makers’ Perceptions

Abstract

Decision makers often do not easily understand the decision space, i.e. the available alternatives and relations among their attributes. Misunderstanding the relations between attributes might lead to a bad decision. Recent research in decision analysis has addressed this problem and proposed to support decision makers with visual information about the decision space. However, the question of which visualization method and format supports decision makers best is largely unanswered. We focus on coordinate systems as visualization method and investigate the impact of 2D and 3D formats on decision making processes. We show that 3D is not superior to 2D in terms of several decision making performance variables, such as time to make a decision. We, however, provide first evidence that 2D and 3D visualizations differ in the decision makers’ perceptions and that these differences are moderated by the complexity of the decision space.

Keywords: Information visualization, decision support system, decision space, dimensionality, decision making performance, system perceptions
Introduction

Decision makers often face decision making scenarios that are more complex and challenging than decision analysts might expect at a first glance. Assume, for example, a decision maker who is searching for a rental apartment with a large living space. The decision maker might be aware that apartments with a larger living space will require a higher rental price. The decision maker has thus to deal with potentially conflicting attribute relations. A conflicting attribute relation exists, if it is necessary to exchange the outcome of one attribute to attain a higher outcome of another one. In this example, the decision maker’s preference for a larger living space requires accepting losses in another potentially desired apartment attribute, i.e. a low rental price.

It is further likely that the decision maker simply does not know of all conflicting attribute relations that need to be accepted or considered in the search process. Larger apartments might, for example, be either primarily located in the highly frequented city center, which reduces the likelihood of finding an apartment simultaneously offering an also preferred parking lot. It is also possible that large apartments are only located far away from the city center, which requires traveling undesirable large distances to the decision maker’s workplace on a daily basis. Which story is true depends on the individual city structure and is likely to be unknown to the decision maker. Some conflicting attribute relations may be more obvious (e.g., floor space vs. rental price) than others (e.g., floor space vs. parking lot or location). Simply searching for large apartments may lead to dissatisfying results. The decision maker might become aware of this situation, though, most likely after a time-consuming and effortful search and comparison process.

This problem is also known in the scientific literature. Previous studies indicate that knowing the available decision alternatives, related attribute combinations and conflicting attribute relations cannot be presumed, but may be beneficial in the decision making process (Butler et al. 2008; Hoeffler and Ariely 1999; Huber and Klein 1991; Keeney 2002). In the following we refer to the information about the available decision alternatives and the available attributes as the decision space.

Decision spaces are often complex in real decision making scenarios. In consumer decision making, consumers as a special kind of decision makers, for instance, consider up to eight rather than two attributes when comparing alternatives for a purchase (Jacoby et al. 1977; Moorthy et al. 1997; Olson and Jacoby 1972; Sheluga et al. 1979). This increases the number of attribute relations describing the decision space from 1 to 28 (= 8(8-1)/2). As these studies show, consumers do even consider less than eight attributes in many cases. Other decision making scenarios, such as managerial decision making, can easily comprise more than eight attributes and surpass the level of complexity prevalent in consumer decision making. Since we focus on consumer decision making in this study, higher levels of complexity are beyond the scope of this research.

Decision makers using a decision support system might benefit from getting information on the decision space, since this information helps to recognize and incorporate complex relations into their decision making process. Supporting the decision making process can i) reduce the decision making effort required for processing information on and the comparison of decision alternatives, ii) improve the quality of the decisions induced by the system’s recommendations (e.g., in terms of choosing non-dominated alternatives or the decision makers’ subjective evaluation of the recommendations) and iii) the decision makers’ perceptions and subjective evaluations of the decision support provided by a decision support system (Xiao and Benbasat 2007).

Providing decision makers with additional information, however, does not come without threats. Due to the limited cognitive capacities to process information (Payne et al. 1993), supporting decision makers with additional information might lead to information overload and might thus reduce the quality of decisions (Lurie 2004). If information is, however, provided in a visual form like graphs or pictures, the decision makers’ perceptual system can easily encode this information (Lohse 1997; Zhang and Whinston 1995). Decision makers are able to extend their information processing capacities and reduce the threat of information overload (Lohse 1997; Tegarden 1999; Zhang and Whinston 1995). It is hence important to support decision makers with information on the available alternatives and attribute relations, but it seems to be even more important to support them with the right visualization type.

Information visualization has gained popularity as it seems to be a plausible way to support decision makers efficiently with information on decision making scenarios (Lurie and Manson 2007; Turetken and
Sharda 2001). Information visualization is defined as the transformation and presentation of information using a visual medium (Lurie and Manson 2007). It makes use of the human ability to transform visual cues like detected patterns or differences in shape or color of visual objects into knowledge (Kosslyn 1994). Previous research developed different visualization types to support decision making, such as tables, coordinate systems or bar graphs (e.g., Kumar and Benbasat 2004; Theetranont et al. 2007; Tractinsky and Meyer 1999). In this study, we focus on coordinate systems as visualization type that is easy to interpret, since decision makers are typically familiar with coordinate systems. We are especially interested in analyzing the effects of the visualization dimensionality (2D vs. 3D) of coordinate systems that provide information about decision spaces on decision maker’s decision quality, decision effort and their perceptions.

A review of previous studies comparing 2D and 3D visualizations reveals a gap in the literature: there is mixed evidence on the question whether 2D or 3D visualizations provide superior decision support. The choice of the right visualization format is important, since inappropriate decision support may lead to a decrease in decision quality (Xiao and Benbasat 2007), which might be costly when it comes to management decisions. Shopping websites may further lose customers, since inappropriate decision support has been shown to reduce the intention of consumers to adopt decision support systems for future use (Xiao and Benbasat 2007). Further, the effects observed by prior research might not be complete as the decision support of 2D and 3D visualizations has primarily been compared and evaluated using measures regarding the observable decision making performance (i.e., time to make a decision, objective decision quality). Recent research, however, cites evidence that modifications to a decision making process are likely to affect a wide range of user perceptions regarding the decision support (Xiao and Benbasat 2007).

We contribute to recent research by investigating whether the 2D or the 3D visualization format provides better decision support in simple or complex consumer decision making scenarios. We evaluate the quality of the decision support in terms of i) observable decision making performance and ii) decision makers’ perceptions of the decision support process. In a laboratory experiment, we ask the study participants to use one of four decision support systems providing visual information about the decision space to search for a digital camera for purchase. To observe the interplay of dimensionality and decision making complexity in case of consumer decision making, we compare both visualization formats in i) a simple purchase decision scenario (alternatives are described by four attributes) and ii) a complex purchase decision scenario (alternatives are described by eight attributes). Overall, we use four treatments: i) 2D/four attributes, ii) 3D/four attributes, iii) 2D/eight attributes and iv) 3D/eight attributes. We collect data on the decision making performance in terms of effort and quality and the participants’ perceptions of each decision support system.

The remainder of this article is organized as follows: In the next section, we relate our work to prior studies comparing 2D and 3D visualizations and describe our contribution in more detail. We then explain the visualization method applied to our study. We thereafter describe our empirical investigation and the results of the laboratory experiment. Finally, we discuss the implications for practice and future research.

**Related Work**

In the following section, we briefly review previous studies that compare 2D to 3D visualizations. Existing studies fall into three categories: i) studies generally supporting the predominance of either 2D or 3D visualizations, ii) studies finding mixed evidence on the value of 2D versus 3D visualizations and iii) studies recommending the use of a specific format (either 2D or 3D) depending on specific conditions. Table 1 summarizes the findings of our literature review.

There are only a few studies that clearly prefer one visualization format. Pilon and Friedman (1998) compare the efficiency of the search for specific objects in 2D and 3D visualized environments, concluding that 2D visualizations enable more efficient searches than 3D visualizations. In contrast, the studies of Dull and Tegarden (1999) and Kumar and Benbasat (2004) recommend using 3D rather than 2D visualizations. Dull and Tegarden (1999) investigate the impact of 2D, 3D and rotatable 3D visualizations on decision makers’ effort and decision quality. They find that 3D visualizations help making better decisions without decreasing the time required for decision making. Only the comparison of 2D to a
rotatable 3D visualization leads to reduced decision making time. The study of Kumar and Benbasat (2004) focuses on the interaction of graph complexity (nine and 25 data points displayed) and the task type (pattern and trend recognition and extraction of concrete data values) on the comprehension effort, i.e., the time taken to comprehend specific information from 2D versus 3D visualizations. In their conclusion, Kumar and Benbasat (2004) clearly recommend using 3D over 2D visualizations, since 3D visualizations allow processing information quicker in all cases, independent of task type and graph complexity.

### Table 1. Prior Studies Comparing 2D and 3D Visualizations

<table>
<thead>
<tr>
<th>Source</th>
<th>Decision Task</th>
<th>Visualization Type</th>
<th>Performance Measures</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pilon and Friedman (1998)</td>
<td>Object retrieval</td>
<td>2D and 3D objects</td>
<td>Effort</td>
<td>2D is superior</td>
</tr>
<tr>
<td>Dull and Tegarden (1999)</td>
<td>Forecasting</td>
<td>2D and 3D line graphs</td>
<td>Effort and quality</td>
<td>3D is superior</td>
</tr>
<tr>
<td>Kumar and Benbasat (2004)</td>
<td>Graph comprehension</td>
<td>2D and 3D line graphs</td>
<td>Effort</td>
<td>3D is superior</td>
</tr>
<tr>
<td>Zhu and Chen (2005)</td>
<td>Knowledge retrieval</td>
<td>2D and 3D geographic maps</td>
<td>Effort and quality</td>
<td>Mixed evidence</td>
</tr>
<tr>
<td>Kim et al. (2011)</td>
<td>Task fulfillment</td>
<td>2D and 3D cell phone menus</td>
<td>Effort and user perceptions</td>
<td>Mixed evidence</td>
</tr>
<tr>
<td>Nah et al. (2011)</td>
<td>Task fulfillment</td>
<td>2D and 3D virtual world environments</td>
<td>User perceptions</td>
<td>Mixed evidence</td>
</tr>
<tr>
<td>Van der Land et al. (2013)</td>
<td>Graph comprehension and group decision making</td>
<td>2D and 3D virtual world environments</td>
<td>Effort, quality and comprehension</td>
<td>Mixed evidence</td>
</tr>
<tr>
<td>Lee et al. (1986)</td>
<td>Managerial decision making</td>
<td>2D and 3D scatter grams and block diagrams</td>
<td>Effort and quality</td>
<td>Depending on the information format</td>
</tr>
<tr>
<td>Tractinsky and Meyer (1999)</td>
<td>Situational visualization choice</td>
<td>Table, 2D and 3D graph</td>
<td>User perceptions</td>
<td>Depending on visualization purpose</td>
</tr>
<tr>
<td><strong>This study</strong></td>
<td>Consumer decision making</td>
<td>2D and 3D coordinate systems</td>
<td>Effort, quality and user perceptions</td>
<td>Depending on complexity</td>
</tr>
</tbody>
</table>

The vast majority of studies, and especially studies in the recent past, provide rather mixed evidence and do not make general recommendations for the use of a specific visualization format. Zhu and Chen (2005) shed light on the question whether the visualization format (2D versus 3D) impacts the effort and the quality of conveying spatial knowledge in a geographical information visualization system. They did not find a consistent performance difference between 2D and 3D visualizations in conveying declarative, configurational or procedural knowledge. The study of Kim et al. (2011) compares 2D and 3D cell phone menus with respect to task performance in terms of time required for task fulfillment and user perceptions in terms of perceived space use, fun of use and satisfaction. They find evidence that users need less time to find specific menu entries in large menus using 2D menus, but there is no difference in task performance for smaller menus. They further find mixed evidence with respect to user evaluations of 2D and 3D menus for different menu sizes. Nah et al. (2011) examine 2D and 3D virtual environments, and especially the impact of dimensionality on user telepresence, enjoyment, brand equity and the behavioral intention. They observe that users do enjoy 3D virtual worlds more than 2D, but 3D virtual worlds lead to lower brand equity. Finally, Van der Land et al. (2013) investigate the understanding of objects and the performance of group decision making in 2D and 3D virtual environments. They conclude that 3D visualizations are more effective in supporting the understanding of individuals and groups, but reduce the efficiency of group decision making.
Two further studies provide implications regarding the use of 2D and 3D visualizations depending on certain conditions. First, Lee et al. (1986) consider the influence of different information formats (continuous and discrete data) on the performance of decisions when decision makers are supported by 2D and 3D visualizations. The study provides evidence that 3D visualizations help improving the quality of decisions at a constant effort in case of information is continuous. 2D visualizations provide better decision support when visualizing discrete information. Tractinsky and Meyer (1999) focus on the interaction of the visualization purpose (decision support and impressing others) and desirability of the information content (e.g., negative information about oneself) with an individual’s visualization choice for that specific purpose (2D bar graph, 2D bar graph augmented by perspective, 3D bar graph and tables). They find that 2D visualizations are preferred for decision making scenarios over 3D visualizations. 3D visualizations are rather preferred for the purpose of impressing others, especially when the content of the information provided was undesirable for the individual.

In summary, we can draw two conclusions from the review of prior work: First, prior studies primarily compared 2D to 3D visualizations focusing on decision making performance in terms of decision making effort and the quality of the decisions made. Second, previous research provides mixed evidence on the question whether 2D or 3D visualizations provide superior decision support and is, with except of Lee et al. (1986), lacking clear advice regarding the use of a specific format for decision making.

We address this research gap by investigating the decision support of 2D and 3D coordinate systems in simple and complex consumer decision making scenarios. More specifically, we evaluate the decision support of 2D and 3D coordinate systems in terms of decision making performance (comprising effort and quality of the decisions) as well as commonly applied user perception measures from information systems research. We use several different perception measures in order to better understand when and why a specific visualization format (2D or 3D) should be preferred. In the following section, we briefly describe how the visualizations applied in this study (2D and 3D coordinate systems), support decision makers in simple and complex consumer decision making scenarios by providing relevant information on their decision task.

**Visualization Method**

Coordinate systems can provide meaningful information about decision spaces to assist the process of decision making. As a simple example, assume a decision space for rental apartments where apartments are described by the two attributes living space and rental price. Apartments with a larger living space typically come at a higher rental price. We can visualize information about this decision space in a 2D coordinate system as plotted in Figure 1; i.e., by assigning each apartment attribute to one axis of the coordinate system and depicting rental apartments using their attribute combination as coordinates. Apartments (represented by the red dots in Figure 1) will be plotted the farther on the right, the higher the floor space and the farther in the upper region of the coordinate system, the higher the rental price of an apartment.

![Figure 1. Example of a 2D Coordinate System](image)

A decision maker using this visualization to support the search for a suitable rental apartment can retrieve essential information about the decision space, that is: i) the available decision alternatives (apartments),
ii) its attribute level combinations and iii) relations among the apartment attributes. Attribute levels of the available apartments are represented by the coordinates of the apartments in the coordinate system. Apartments in the lower left corner of the visualization in Figure 1 are small and cheap whereas apartments in the upper right corner are large and expensive. The visualization hence enables a decision maker to easily compare the attribute combinations of multiple decision alternatives. A decision maker can further become aware of the relations among the attributes. The visualization clearly indicates that apartments with a higher floor space are available at a higher rental price. Floor space and rental price thus form a conflicting relation with respect to the given decision space. A decision maker can use the information inferred from the visualization and incorporate them into his/her decision making process.

In this study, we aim at comparing 2D and 3D coordinate systems in simple and complex consumer decision making scenarios. We define the complexity of a decision making scenario by the number of product attributes a decision maker considers when comparing alternatives. Our example is limited to only two attributes. Theetranont et al. (2007) proposed the application of a 3D coordinate system to visualize decision spaces consisting of three attributes. Several decision situations are described by more than three attributes and decision makers are willing and able to also consider more than three attributes. Consumers as a special instance of decision makers use up to eight attributes when making a complex purchase decision (Jacoby et al. 1977; Moorthy et al. 1997; Olson and Jacoby 1972; Sheluga et al. 1979). To support complex consumer decision making scenarios, 2D and 3D coordinate systems need to be prepared for providing information about higher dimensional decision spaces (i.e., more than 3 dimensions) that contain information about the relations among any required number of attributes and the decision alternatives. To enable displaying more than three dimensions in a coordinate system, a dimensional reduction of the decision space is required.

We suggest singular value decomposition (SVD) for reducing dimensions. SVD is the standard approach for linear dimension reduction (Zhang et al. 2007) and is, for example, used to compute a principal component analysis and to extract GAIA planes to visually plot decision spaces (Brans and Mareschal 1994). It allows reducing any dimensional spaces to two or three dimensions while maximizing the preserved variance of the data (Härdle and Simar 2003). For our study, the SVD reduces a high-dimensional decision space to a two or three dimensional visual representation, ensuring that the relations among the decision alternatives and up to eight attributes are interpretable in a meaningful manner.

In the following paragraphs, we briefly explain the process of dimension reduction and arriving at a visual representation of the decision space using SVD. We explain the visualization process using the decision space for rental apartments as an example. The SVD process usually starts with a data matrix containing information about two variables. These two variables are here the decision alternatives and the attributes describing the alternatives which jointly constitute the decision space. Assume a decision space consisting of four rental apartments (A1, A2, A3, and A4) that are described by four attributes (rooms, furnishing, location, and price). The cells of the data matrix $x_{ij}$ in Table 2 contain normalized information about the decision space, i.e., the levels of the attributes $j$ of each alternative (apartment) $i$. The normalization yields a uniform operationalization of attribute levels so that low levels of $x_{ij}$ represent low or undesirable attribute levels (e.g., a low number of rooms or a high price) and vice versa.

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Rooms</th>
<th>Furnishing</th>
<th>Location</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>5</td>
<td>7</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>A2</td>
<td>4</td>
<td>5</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>A3</td>
<td>7</td>
<td>3</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>A4</td>
<td>8</td>
<td>2</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

1 The major difference between GAIA planes and our visualization method is the rescaling of the data points (i.e., alternatives and attributes). With the rescaling method used in our study (see Equations 2 and 3), it is possible to not only interpret the distances between alternatives and the distances between attributes but also the distances between alternatives and attributes.
The decision space consists of four dimensions (i.e., alternatives are described by four attributes). A visual representation of the relations among the rental apartments and the apartment attributes thus requires a reduction to two or three dimensions. The data matrix (Table 2) will be first transformed into a standardized matrix $Z$. $Z$ is then decomposed into the three following components (Härdle and Simar 2003): i) a diagonal matrix $\Sigma$ containing $K$ singular values, such that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_K$, which are used to extract the number of desired dimensions for the visual representation; ii) a $\Gamma(I \times K)$ matrix which contains information that is required to calculate the coordinates of the alternatives $i$ ($\Gamma$ contains the eigenvectors of $ZZ^T$); and iii) a matrix $\Delta(J \times K)$ containing information that is required to derive the coordinates of the attributes $j$ ($\Delta$ contains the eigenvectors of $Z^TZ$). Equation 1 describes the SVD of matrix $Z$.

$$Z = \Gamma \Sigma \Delta^T$$  

(1)

The SVD uses the information described in Equation 1 to compute two separate visual parts: i) one part containing standard coordinates for each alternative $i$ which reflects the relations among the alternatives, and ii) one part containing standard coordinates for each attribute $j$ which represents the relations among the attributes, where $k$ represents the number of the visual dimensions of a coordinate. However, interpreting alternatives and attributes, i.e., deducing the attribute combination of an alternative from its position relative to the attribute points in the coordinate system, is not possible based on these standard coordinates. The standard coordinates are thus rescaled to allow a meaningful joint interpretation of both visual parts. If both variables are to be interpreted jointly, Greenacre (2007) suggests a symmetric rescaling. Equation 2 thus yields the final and rescaled coordinates for each alternative $i$, while Equation 3 yields the coordinates for each attribute $j$, where $k$ is the number of visual dimensions ($k = 1$ is the first dimension, $k = 2$ is the second dimension and $k = 3$ is the third dimension).

$$r_{ik} = \frac{\gamma_{ik} \sigma_k}{\sqrt{p_i}}$$  

(2)

$$c_{jk} = \frac{\delta_{jk} \sigma_k}{\sqrt{p_j}}$$  

(3)

We extracted the first two singular values ($\sigma_1$ and $\sigma_2$) of our apartment example to generate a 2D visualization of the apartment decision space (see Figure 2).

![Figure 2. Relationship between Attributes and Alternatives](image)

A decision maker can use the 2D coordinate system depicted in Figure 2 to retrieve essential information about the decision space, that is: i) the available decision alternatives (apartments), ii) its attribute combinations and iii) the relations among the apartment attributes. Decision makers can interpret the distance between alternatives (represented by the red dots in Figure 2) in the following way. The closer
the points of two alternatives, the more similar are the corresponding apartments. The distance between
alternatives and attributes (represented by the cyan dots in Figure 2) is interpretable in a similar manner.
The closer a particular alternative to a particular attribute, the better the alternative fulfills that attribute
(e.g., apartment 4 has the highest number of rooms and is hence plotted most closely to the attribute
rooms). Finally, decision makers can infer conflicting relations among attributes by interpreting the
distances between pairs of attributes. A greater distance indicates more conflict between two attributes
(e.g., furnishing and rooms), and thus indicates a low probability of finding an alternative that fulfills both
attributes equally.

Reducing the number of dimensions causes an information loss. We define this information loss as the
amount of variance lost when reducing dimensions. Or in other words, the relations among the decision
alternatives and attributes in the visualization may not perfectly coincide with the relations in the original
decision space. Since each dimension of the decision space originally represents one attribute, the
information loss is primarily affected by the interplay of the number of attributes that constitute the
decision space and the visualization format (2D vs. 3D). The information loss increases with an increasing
number of original dimensions and a decreasing number of extracted visual dimensions. This forms an
interesting interaction between the complexity of a decision space (i.e., its dimensionality) and the
dimensionality of the visualization generated to plot the decision space. The next section describes the
laboratory experiment we conducted to investigate this interaction.

Empirical Investigation

The complexity of a decision making scenario and the dimensionality of a visualization as well as the
interaction of both parameters are likely to affect the quality of the decision support which the particular
visualization can provide. On the one hand, 2D coordinate systems have a limited ability to display
information compared to 3D coordinate systems, since they have one fewer dimension to display relations
among attributes and decision alternatives. The information loss will thus always be higher for 2D than
for 3D coordinate systems. On the other hand, 2D coordinate systems are less complex to understand
than 3D coordinate system especially if they are plotted on a 2D screen (Dull and Tegarden 1999). Whereas
the complexity to understand a 2D or 3D coordinate system is independent from the
dimensionality of the decision space, the information loss of a visualization does also depend on the
dimensionality of the decision space (i.e., the number of attributes describing the decision space). We thus
compare 2D and 3D coordinate systems with a varying dimensionality of the decision space in a
laboratory experiment. The next sections describe the research methodology used for our empirical
investigation, the treatments, measures and the experimental procedure.

Research Methodology

We conducted a laboratory experiment examining a consumer decision making situation with a 2x2
between-subjects design to investigate the interaction of visualization formats (i.e., the number of visual
dimensions) and decision complexity (i.e., the number of dimensions in the decision space). Specifically,
we tested two visualization formats (2D vs. 3D) and two dimensional levels of the decision space (4 vs. 8
attributes) to distinct between simple and complex consumer decision making scenarios. In order to
investigate the interaction of visualization format and decision space complexity, we describe products
with four attributes to create a simple situation in which the comparison of products is easy. Since our
experiment uses a consumer decision making scenario, we derive complex situations from the level of
complexity that is prevalent in consumer decision making scenarios. Recent studies indicate that
consumers consider up to eight attributes when making a purchase decision (Jacoby et al. 1977; Moorthy
et al. 1997; Olson and Jacoby 1972; Sheluga et al. 1979). We thus use eight attributes to create a complex
situation.

During the experiment, the participants had to complete a certain search task: They were instructed to use
a decision support system to find a digital camera matching their individual preferences. We decided to
use a student sample for convenience reasons because there is no a priori reason why students should
behave differently in such a setting than other participants and we are interested in the differences
between the treatment groups and not in absolute performance and perception values.
Experimental Treatments

We developed four decision support systems as treatments for the laboratory experiment. To ensure that variations in the dependent variables are only referable to modifications in the amount of attributes considered (dimensionality of the decision space) and the visualization format, we constructed the systems as similar as possible.

All systems had access to the same product database. The systems operated on a database with 131 cameras collected from Amazon.com. 79 of them were non-dominated (i.e., there is no camera that is better than the focal camera in at least one attribute and at least equally good in all other attributes). In the treatments with simple decision space, the four attributes photo resolution, optical zoom, camera size, and price were used to describe the cameras. Complex decision spaces additionally consisted of the attributes display resolution, video resolution, number of settings and photosensitivity.

We designed the decision support systems in conformity with decision making principles described in previous research. In line with the two stages of a purchase decision process (Gilbride and Allenby 2004; Hauser and Wernerfelt 1990; Payne 1976), we assume that consumers screen the alternatives using non-compensatory strategies in a first step, then employ compensatory decision rules for a more detailed evaluation in a second step. We base the compensatory (second) step on multi-attribute utility theory which is frequently applied to model and analyze multi-attribute decision scenarios (Keeney and Raiffa 1993; Dyer et al. 1992; Wallenius et al. 2008). The basic idea of this approach is that the overall value \( v(x) \) of a decision alternative is the sum of the single-attribute values \( v_i(x_i) \) of the outcome \( x_i \) of each attribute \( i \), weighted by the importance \( w_i \) of each attribute (see Equation 4):

\[
v(x) = \sum_{i=1}^{n} w_i v_i(x_i)
\]

where \( 0 \leq w_i \leq 1 \), and \( \sum_{i=1}^{n} w_i = 1 \). We used linear single attribute value functions \( v_i(x_i) \) with a value of 0 for the worst attribute level and a value of 1 for the best attribute level. In a recent study, Scholz et al. (2015) cite evidence that linear functions appropriately describe the relationship between the camera attributes used in our experiment and the values participants assign them.

The systems all allowed weighing the attributes after the initial filtering process, using a nine-point scale. We used horizontal sliders initially set to 5 (middle), and participants could increase (decrease) an attribute’s importance by moving the slider to the right (left). Participants thus stated attribute importance weights with direct rating, a method that has been found to be user friendly and highly accurate compared to other methods (Pöyhönen and Hämäläinen 2001). The underlying alternative evaluation model was an additive multi-attribute value model as defined in Equation 4.

All systems filtered camera brand, optical zoom and price in the first (non-compensatory) step. Participants then could state their attribute importance in the second step. Using the filtered subset of alternatives, each system generates a visual representation of the decision space with either two or three visual dimensions. Attributes are represented by circles (2D coordinate system) or bullets (3D coordinate system). A small distance between the attributes indicates a consonant relationship whereas a large distance indicates a conflicting relationship. Rectangles with numbers symbolize the alternatives. We provide representative screenshots in Appendix A.

The only differences between the four systems are then as follows: System 1 and system 2 both operate on a decision space described by four attributes (photo resolution, optical zoom, camera size, and price). They, however, differ in the visualization format: System 1 uses a 2D coordinate system whereas system 2 visualizes the decision space in a 3D coordinate system. Systems 3 and 4 differ from systems 1 and 2 in the number of attributes that describe the decision space. Cameras of systems 3 and 4 are described by eight attributes (photo resolution, optical zoom, camera size, price, display resolution, video resolution, number of settings, and light sensitivity). System 3 plots the decision space in a 2D coordinate system and system 4 in a 3D coordinate system.

Comparing system 1 (2D / 4 attributes) to 3 (2D / 8 attributes) and system 2 (3D / 4 attributes) to 4 (3D / 8 Attributes) enables us to isolate the effect of the decision space complexity on the dependent variables. Comparing system 1 (2D / 4 attributes) to 2 (3D / 4 attributes) and system 3 (2D / 8 attributes) to 4 (3D /
8 Attributes) enables us to analyze the impact of the visualization format (2D vs. 3D) on our dependent variables. Our dependent variables are described in the next section.

**Measures**

We evaluate the decision support of 2D and 3D coordinate systems in simple and complex consumer decision making scenarios based on the framework by Xiao and Benbasat (2007). The measures fall into two categories: decision making performance and user perceptions.

Decision making performance refers to the ability of a decision support system to support a user’s decision making process and encompasses decision effort and decision quality. Xiao and Benbasat (2007) define decision effort as the amount of effort incurred by a user in terms of processing information, comparing alternatives and making a final decision. We operationalize the decision effort of individual users by measuring the time needed from the start of the product search until a final decision is made.

Decision quality is evaluated either objectively or subjectively. Objective decision quality is based on the principle of coherence and typically measured in terms of users’ choices of non-dominated alternatives (Häubl and Trifts 2000; Payne et al. 1993).

Subjective decision quality, in contrast, is evaluated relatively to a user’s preferences and is defined as the degree to which the alternatives considered for purchase match a user’s preferences (Xiao and Benbasat 2007). To measure the subjective decision quality, our participants stated their probability of choosing each of the top 10 recommended alternatives. We compare the participants’ evaluations of the top 10 recommended alternatives with the values the decision support system computed for each of the top ten alternatives based on Equation 4. This enables us to calculate three measures of subjective decision quality: i) the first-choice hit rate, which equals the fraction of cases where the system correctly predicts the user’s most preferred alternative on rank 1 of the recommendation list (Johnson et al. 1989), ii) the user’s rating of the alternative the system predicts on rank 1 and iii) the average probability of choosing each of the top 10 recommended alternatives. Applications of these decision quality measures can also be found in prior studies (Aksoy et al. 2011; Johnson et al. 1989; Diel and Zauberman 2005).

Modifications of a decision making process may also impact the users’ perceptions, that is how users subjectively evaluate the support or interaction with a decision support system during their decision making process. We focus on major information system success indicators: perceived ease of use (PEOU), perceived usefulness (PU), end user’s satisfaction (EUS), reuse intention (RI), and a net promoter score (NPS). PEOU and PU originate from the technology acceptance model (Davis 1989). PEOU is a user’s belief that system usage is free of effort, while PU is a user’s evaluation of how useful the system was in supporting the process of decision making. To determine their satisfaction, users trade off the costs and benefits of system use, which may result in either positive or negative evaluations (Xiao and Benbasat 2007). RI (Davis 1989; Igbaria 1997) covers the user’s desire to keep using the decision support system in the future, after their initial use (Al-Natour et al. 2010; Venkatesh and Davis 2000). Finally, the NPS (Reichheld 2003) is an often-applied management metric that provides an alternative to traditional customer satisfaction measures. It can gauge customer loyalty and their propensity to engage in word-of-mouth activity.

We measured decision making performance and user perceptions by logging our participants’ behavior and by a two-staged questionnaire. All the user perception constructs were measured with multiple items, to ensure a thorough assessment (Churchill 1979). We used seven-point Likert scales, ranging from 1 ("I fully disagree") to 7 ("I fully agree"). We took the PU and PEOU measures from Davis (1989), EUS from Au et al. (2008), and the RI measure from Al-Natour et al. (2010). For the NPS, we relied on the work by Reichheld (2003).

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2 An alternative $X$ is dominated by another alternative $Y$ if $Y$ is better than $X$ in at least one attribute and not worse than $X$ in the remaining attributes (Pfeiffer and Scholz 2013).
**Procedure**

We invited undergraduate and graduate students from the University of Passau, who might be interested in camera offers and assigned them randomly to one of the four treatments. A short video explained the functionality of the decision support system and described the experimental task (see Appendix B). In the beginning of the experiment, the respondents were instructed that they were looking for a new digital camera. Every decision support system used the same database, graphical layout and navigational elements, so any differences in usage behavior, prediction accuracy, and user perceptions result from the experimental treatment – namely, the underlying decision space and the visualization dimensionality.

All systems logged detailed user behavior, and then the respondents completed a two-part questionnaire after finishing their search. First, they indicated their visit probability for the top 10 recommended digital cameras. In all systems, the results appeared ordered by their estimated utility values in a separate list. Second, they completed a questionnaire consisting of items related to their demographics, psychographics, experience level, and usage perceptions.

**Analysis and Results**

The 112 student participants received € 7 (approximately US$ 10 at the time of the experiment) in compensation for their participation. We distributed them evenly across the different treatments (25 in the 2D & four attribute condition, 34 for 3D & four attributes, 27 for 2D & eight attributes, and 26 for 3D & eight attributes). We conducted the laboratory experiment at the University of Passau (Germany) with one instructor running all sessions.

There were slightly more female respondents (51.8%), and the average age was 22.5 years (SD=2.94; min=18, max=31). All constructs were highly reliable with Cronbach's alphas of at least .89. The average time spent browsing for the camera (excluding the experimental instructions and a short learning phase) was about 10 minutes.

**Decision Making Performance**

In order to analyze differences in the decision making performance among the treatments, we used a Gamma regression with respect to search time, a Poisson regression for the number of dominated alternatives considered, a Logit regression for the first choice hit rate, and an Ordered-Logit regression for the rating of the best expected alternative and the mean probability of purchase. We observed that subjects needed significantly more time \( (p < .001) \) when they had information on eight instead of four attributes (see Table 3). This is unsurprising taking into account that more attribute weightings have to be specified. Further, we found moderate but almost always insignificant decision quality differences between the 2D and the 3D visualizations. Table 3 summarizes these results, which are in line with other empirical investigations that also found no differences between 2D and 3D visualizations (e.g., Zhu and Chen 2005). The advantage of lower information loss when using a 3D visualization seems thus negligible if alternatives are described by only a few attributes. Furthermore, 3D visualizations on a 2D panel (monitor) are not as easy to interpret (Dull and Tegarden 1999) and might hence prevent a better decision making performance.

Concerning decision quality, we found no significant differences in the consideration set sizes of our treatments (2D/4 Attributes: 5.32, 3D/4 Attributes: 5.94, 2D/8 Attributes: 5.85, 3D/8 Attributes: 5.50), the number of dominated alternatives, the first choice hit rate, the rating of the best expected alternative and the mean probability of purchase. Taking into account that it is much harder to correctly predict a decision maker's preference in situations where alternatives are more complex, it is surprising at first sight that the predictive validity in terms of first choice hit rate was higher when eight instead of four attributes were used. However, several alternatives might exist that especially differ in the hidden attributes. Products described with fewer attributes are more homogeneous making it more difficult for a decision support system to correctly rank the alternatives. Our results thus indicate no differences in either objective or subjective decision quality between the 2D and 3D visualizations.

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3 The questionnaire used in the experiment is available upon request.
### Table 3. Effects of Search Time and Decision Quality

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Average Search Time in Minutes (SD)</th>
<th># of Dominated Alternatives Considered (SD)</th>
<th>First Choice Hit Rate</th>
<th>Rating of the Best Expected Alternative</th>
<th>Mean Probability of Purchase</th>
</tr>
</thead>
<tbody>
<tr>
<td>2D / 4 Attributes</td>
<td>8.24 (2.97)</td>
<td>1.76 (1.16)</td>
<td>48.0%</td>
<td>6.28</td>
<td>3.50</td>
</tr>
<tr>
<td>3D / 4 Attributes</td>
<td>7.51 (3.82)</td>
<td>2.06 (1.65)</td>
<td>55.9%</td>
<td>6.44</td>
<td>3.86</td>
</tr>
<tr>
<td>2D / 8 Attributes</td>
<td>11.85*** (4.83)</td>
<td>1.59 (1.08)</td>
<td>51.8%</td>
<td>6.07</td>
<td>4.09</td>
</tr>
<tr>
<td>3D / 8 Attributes</td>
<td>10.09* (2.82)</td>
<td>1.65 (1.16)</td>
<td>57.7%</td>
<td>6.15</td>
<td>3.83</td>
</tr>
</tbody>
</table>

Note. *p<.1, **p<.05, ***p<.01.

### User Perceptions

The effects of the systems on users’ perceptions offer novel and interesting insights (Figure 3). If the decision space is simple, 2D visualization outperforms 3D visualization in terms of perceptions. As the complexity increases, perceptions of the 2D visualization decrease, whereas perceptions of the 3D visualization increase.

![Figure 3. Influence of Systems on User Perceptions and First Choice Hit Rate by Number of Attributes](image)

When the decision space consisted of four attributes, 2D visualization appeared significantly more useful (p < .05) than 3D visualization, including the weakly significant, higher EUS (p < .1) and RI (p < .1; Figure 3). The 2D visualization also attracted significantly more promoters (p < .05), though the number of detractors (p > .4) and the PEOU (p > .3) were not affected by the visualization method. Therefore, users preferred the 2D visualization when the number of attributes was reasonably small – similar to the results reported by Tractinsky and Meyer (1999). For more complex products, this difference diminished in all user perception measures and became insignificant (p > .2). Specifically, perceptions of 2D visualization decreased with the number of attributes, but perceptions of 3D visualization increased with a growing number of attributes in the decision space.

### Discussion

### Implications

Decision makers often have to deal with cognitively challenging decision making scenarios since information on many product alternatives and attributes need to be processed to arrive at a final choice (Xiao and Benbasat 2007). This information is often complex because consumers have to take conflicting...
attribute relations into account, meaning that a preference for one attribute may cause losses with respect to other and eventually also desirable attributes. In complex consumer decision making scenarios, consumers take up to eight attributes into account and thus need to be aware of up to 28 attribute relations. Previous literature recognizes that knowing the decision space cannot be presumed and indicates that: i) knowing the decision space and getting familiar with the relations among attributes can help decision makers to construct more stable preferences which may ultimately lead to improved decision making performance (Butler et al. 2008; Keeney 2002; Huber and Klein 1991; Hoeffler and Ariely 1999) and ii) presenting visual information about decision spaces might be an appropriate way to provide consumers the required information while preventing them from information overload (Lurie and Manson 2007; Turetken and Sharda 2001).

Our literature review reveals an important gap in prior research regarding the question in which format information for decision support should be visualized. We find that: i) there is mixed evidence on the question whether 2D or 3D visualizations provide superior support for decision makers and ii) the majority of the studies rather evaluated decision support in terms of decision effort and quality thus neglecting decision makers' perceptions of the systems that assist during their decision making. In this study, we shed light on this research gap by investigating the decision support of 2D and 3D coordinate systems in simple and complex consumer decision making scenarios. We evaluate the decision support using both decision making performance and decision makers' perceptions.

To evaluate the interplay of decision making complexity and the decision support of the visualization format, we conducted a laboratory experiment on a consumer decision making task. We tested four decision support systems that provided decision makers with visual information: a 2D and a 3D coordinate system in a simple consumer decision making scenario (decision space consists of four attributes) and in a complex scenario (decision space consists of eight attributes). We demonstrated that a 2D visualization is perceived as superior to 3D when the decision objects are described by only a few attributes. We do not observe this difference in terms of objective performance measures such as the time needed to make a decision or the decision quality. Interestingly, our results thus indicate that decision making performance and user perceptions are not necessarily correlated and that an evaluation of visual decision support should consider both the users' perceptions and the users' behavior.

Our results offer implications for research and practice in terms of consumer decision makers and providers of decision support systems, such as online recommender systems. The comparison of the 2D and 3D visualizations revealed no significant differences in terms of decision quality. However, 2D visualizations prompted greater perceptions of ease of use and usefulness, as well as higher satisfaction, when only a few attributes were depicted. With eight attributes though, we found no significant effect of user perceptions between 2D and 3D visualization. We recommend using 2D visualizations only if the decision space is described by few attributes. These results also indicate that providers of decision support systems, such as online retailers providing recommender systems, should evaluate their systems based on decision makers' observable behavior (e.g., consideration set size, choice probability, time to make a decision) and decision makers' perceptions (e.g., perceived ease of use, end user satisfaction).

This study extends prior research by a novel finding. The complexity of a decision situation moderates the evaluation of a visualization format (2D vs. 3D), but only those evaluation measures that reflect decision makers' perceptions. Existing research has mainly focused on decision makers' observational behavior and found no clear support for any visualization format in most cases. Our results support this finding, but also demonstrate that the decision makers' perceptions differ from observational data and make a 2D visualization superior if the decision situation is rather simple.

**Limitations and Future Research**

This research is subject to some limitations that we summarize in the following. One limitation is the use of a convenience sample in our laboratory experiment. However, there is no a priori reason why students should behave differently in such a setting than a representative sample. Each participant might also have eliminated a different number of alternatives which leads to different visual projections of the decision space. However, the number of alternatives that remains in the decision space after the initial filtering step is not significantly different across the treatments on average (tested with ANOVA, F=0.604, p=0.614). We thus assume that the initial filtering has had approximately the same effect on all treatments. Furthermore, we provided rank numbers for the recommended decision alternatives when
observing consumer choices. Providing predictive ratings tends to anchor users’ evaluations of the recommendations (Cosley et al. 2003). Since we provided predicted ranks in all four treatments, the effect is hence equal for all treatments and we have no indication that this effect has changed the differences between the treatments in terms of the system quality or the users’ perceptions. We believe these limitations do not limit the generalizability of our results, especially since we are interested in the differences between treatments instead of absolute values.

We also define complex decision making scenarios by the maximum number of product attributes considered when making a purchase decision. In managerial decision making scenarios, it is possible that even more than eight attributes are considered by a decision maker. The implications of our paper are restricted to the level of complexity that is found in consumer decision making scenarios. Higher levels of complexity are beyond the scope of this work but provide avenues for future research.

Finally, depicting high dimensional decision spaces in 2D or 3D visual representations requires reducing the dimensionality, which might lead to information loss and thus erroneous interpretations. This is especially critical in case of higher information loss. We calculated the information loss as percentage of the variance that is not covered by the two or three dimensions that were used for the visualization. We found an information loss of 20.6% on average across our treatments and a maximal information loss of 35.0% indicating that the visualizations presented the decision space rather accurate. It should, however, be mentioned that low dimensional visualizations of high dimensional decision spaces may help decision makers to get information on the available alternatives, their attribute combinations and potentially conflicting attribute relations. When it comes to the final choice among decision alternatives, the visual representations of the decision space used in this study cannot replace a comparison of the real attribute values of the decision alternatives. Our decision support systems thus listed all cameras depicted in the visual representation of the decision space in a separate panel. Each camera is here described with its levels of all four/eight attributes.

**Conclusion**

The results of our study suggest an interesting trade-off: 3D visualizations preserve more of the original information about the decision space than 2D visualizations. However, users often express some initial reluctance toward 3D visualizations, apparently because of the complex interpretations it demands, including information occlusion and ambiguous depth judgments (Kumar and Benbasat 2004). From a managerial point of view, our results suggest the use of 2D visualization when the number of attributes is rather small, which implies only moderate information loss. If the number of considered attributes increases, 3D visualization becomes more attractive, because the information loss is now more relevant. The lower information loss of 3D visualizations slightly improves decision making performance, and ultimately enhances user perceptions. People seem to prefer 2D visualizations because it is easier to understand, but the advantages of 3D visualizations can compensate for this initial reluctance with better results, which ultimately gets reflected in terms of user perceptions. Figure 4 illustrates this classification of visualization methods in the trade-off between information loss and user perceptions.

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**Figure 4. Classification of Visualizations in the Trade-Off between Information Loss and User Perceptions**
Appendix

Appendix A: Treatments

System 1: 2D / 4 Attributes

System 2: 3D / 4 Attributes

System 3: 2D / 8 Attributes

System 4: 3D / 8 Attributes

Figure A.1. Screenshots of the Systems
Appendix B: Experimental Instructions

The following paragraphs contain the experimental instructions for system 1 (2D / 4 attributes). The modifications of the instructions for systems 2 to 4, i.e. when the visualization contained information on eight instead of four attributes or the visualization format was 3D instead of 2D, can be found in the brackets.

“Welcome and thank you for your attendance. Today, each of you will use a recommendation system to search for a digital camera matching your individual preferences. Now, we will briefly explain how the recommendation system works. The search for a digital camera will proceed in two steps. In the first step, digital cameras that do not meet your preferences can be filtered out upfront on the initial page. According to the default settings, the recommendation system searches for suitable digital cameras among all available brands. You can also restrict the search on certain brands by selecting them from the list on the left. Additionally, you can exclude digital cameras from the search results that have, for example, an undesirable zoom factor or an undesirable price. To do so, just set an upper and/or lower limit for the corresponding attributes or leave these fields empty when you do not want to set a restriction. By clicking the "Forward" button, you will be forwarded to a second search page.

On this next page, a list will display the digital cameras that meet your search criteria on the right side of the interface. The digital cameras are described by the attributes that could be restricted in the previous step. You can sort the digital cameras according to your personal preferences. Use the sliding controllers on the left to specify the importance of each of the four (eight) attributes "Photo Resolution", "Optical Zoom", "Camera Size" and "Price" (for 8 attributes additional: "Display Resolution", "Video Resolution", "Number of Settings" and "Light Sensitivity") that describe the digital cameras.

For a better understanding of the remaining digital cameras, a visualization containing information about four (eight) camera attributes and the first ten search results is displayed in the middle of the interface. Digital cameras are displayed as rectangles (3D: cubes). The particular camera attributes are depicted as circles (3D: bullets), where the size of a circle (3D: bullet) represents the importance that is adjusted for that particular attribute. Further, the proximity between attribute circles (3D: bullets) can be interpreted. If two circles (3D: bullets) are depicted afar, it is unlikely that a digital camera contains both attributes at high levels. In this example the circle (3D: bullet) "Camera Size" is depicted afar from "Optical Zoom". So, digital cameras will be either small or have a high optical zoom. It is not very likely to find a small digital camera simultaneously offering a high optical zoom. The proximity between camera attributes and distinct camera rectangles (3D: cubes) can also be interpreted. A digital camera contains attributes at high levels whose corresponding circles (3D: bullets) are depicted in close proximity and low levels of attributes that are depicted afar. The camera rectangles (3D: cubes) are labeled by numbers referring to their corresponding rank in the results list on the right side. Pointing with the mouse on an attribute circle (3D: bullet) dyes attribute bullets in green that are close and thus conceivable in combination and distant and inconceivable attributes in red. Further, a small popup appears beside the selected attribute circle (3D: bullet) where conceivable and inconceivable attributes are also listed. If you point with the mouse on a camera rectangle (3D: cube), a popup appears beside the corresponding camera where all available camera attributes are listed.

Finally, if you want to inspect more than the ten top-rated digital cameras, a click on the "Forward" button at the bottom of the interface shows the next ten search results. If you further want to reset your search specifications on the first page, please use the link at the top and not your browser's backwards button. As soon as you found a suitable digital camera and finished your search, please specify the likelihood that you would purchase each of the first ten digital cameras on the list. Use the sliding controller below to state your purchasing probability for the corresponding digital camera. And finally, please click on the button labeled "Survey" displayed at the bottom of the interface. You may now switch on the monitors and start your search for a digital camera.”

References


