Can consumer software selection code for digital cameras improve consumer performance?

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Abstract

Forecasting the performance of products undergoing rapid technological change requires data and the knowledge to interpret that data. We surveyed students about one such product – digital cameras – and found that they lacked knowledge to interpret the data. To show that decision aids could improve their performance, we created a digital camera selection code that included an education module and in an experiment demonstrated its superiority to (1) the recommendations of sales clerks, (2) the recommendations of digital camera owners, and (3) the recommendations of subjects with Internet access, but without access to our code.

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1 Introduction

Consumers buy products for future consumption and must predict product performance. This has become increasingly difficult because with accelerating technological change, modern consumers face a market with products with new features, if not genuinely new products. For example, the 20th century saw the advent of radio, television, VHS, DVD, digital cameras, personal computers, and cell phones. In addition, advancing production technology enables manufacturers to create a wide variety of products for niche markets creating large numbers of alternatives for consumers. For example, there are currently over one hundred and fifty new models of digital cameras on the market. A consumer must forecast both the relative performance of different niches and the alternatives within the niche she selects.

The faster the rate of technological change and the longer the gap between repeat purchases, the less a consumer can rely on prior experience and the more data a consumer must collect for forecasting. Such data includes specification sheets, brochures, salespeople's advice, reviews in books, magazines, and websites, users' opinions, and product interactions. In Section 2, we specify what data consumers could acquire in order to forecast digital camera performance, and we argue that the information value of data is positively related to its reliability and power to discriminate and negatively related to its processing cost. We also show that the demand for data is dwarfed by the amount of data that could be acquired.

In Section 3, we study the procedures that students use to select a digital camera. We focus on two aspects of their selection procedures: how much data they consider and what decision rules they employ to reach to their final selection. In Section 4, we discuss improving consumer search through better software aids.

In Section 5, we discuss our approach to design better digital camera search software. Our selection process aims to first find a small set of quality cameras with the features to take the type of pictures the consumer wants. We assume that consumers have knowledge about what type of pictures they want to take, but general lack knowledge about which features are needed for the intended photo shoots. To help consumers map needed features for intended use, part of this code is an education module. In the final part of the code, the user is presented with alternatives to find the preferred item from the small set. To gain quick access to the codes used in this paper go to http://www.eco.utexas.edu/Homepages/Faculty/Norman/code.html.

We present our experiment and the results in Section 6. We focus on the first decision process, finding a small set of quality cameras with the required features. We found that the subjects using our digital camera selection code performed statistically better than salespeople in a digital camera store, subjects with the Internet access, but not our code, and subjects who owned a digital camera.

In Section 7, we present our conclusions from this procedural consumer study. This is the fourth paper in our efforts to create a theory of a procedural consumer. The other papers are Norman et al (2001), Norman et al (2003), and Norman et al (2004).

2 Data, Information, and Forecasting

In search for a preferred item in a large set of alternatives undergoing rapid technological change such as digital cameras, a consumer generally use rules of increasing implementation cost:

1. Selects a subset of alternatives to consider, Norman et all (2001). This subset could be the digital cameras at a store or Internet site, a type such as a DSLR camera, or a brand such as Canon. These rules can be applied with one observation per set.

2. Uses noncompensatory rules to reduce the set to a small number of alternatives Payne (1976). Noncompensatory rules are rules that do not involve tradeoffs. An example would be all cameras at a store that have a telephoto lens. It could also involve quality judgement like selecting Canon cameras over Casio cameras. This stage can be viewed as selecting a quality

set of cameras with the required attributes for the intended use. These rules require one observation per alternative.

3. Uses compensatory rules, which involve tradeoffs, on the small set to find the preferred item. These rules generally have higher costs than noncompensatory rules, Payne (1976). A consumer could find the preferred item by talking with friends or salespeople, reading digital camera reviews either in magazines or online, or comparing photograph galleries of the respective cameras online. These rules require more data for more attributes and more processing.

There are instances where consumers go directly from the market to the final selection without considering any alternatives so this breakdown applies generally, but not in all cases.

In cases when prior experience is insufficient, consumers collect data from 2^{nd} and 3^{rd} parties. In considering markets with a large number of alternatives with a rapid rate of technological change, we shall define:

- 1st parties: Consumers
- 2nd parties: Producers and sellers of product
- 3rd parties: Organizations that provide data, but do not directly sell products. (Such online sites may pass viewers through to PriceGrabber.com, where viewers can link to sites that do sell the product)

The greater the rate of technological change, the less valuable is prior experience, and the more data that must be collected. For example, for a product undergoing rapid technological change, such as a digital camera, a consumer generally will have to collect data at step 2 above.

Producers and sellers have incentives to provide consumers with product data and to a very limited degree enable consumers to test the product, as with a car test. Because millions of consumers search for similar goods, there are tremendous economies of scale for third parties to provide consumers with better data and the knowledge to interpret that data. For decades, entrepreneurs have created "how to" books and trade magazines, providing reviews of technological products such as automobiles and electronic devices. Two such digital camera trade magazines are Popular Photography and Digital Camera World. With the rise of the Internet, entrepreneurs have created numerous sites to provide consumers with decision support for technology products, especially in electronics. For digital cameras, a consumer can go to sites such as CNET.com, Consumerreports.org, Megapixel.net, DCResource.com, DPReview.com, Imaging-resources.com, and Steves-digicams.com. Such websites provide some or all of: (1) digital camera overview articles, (2) tables of camera attributes, (3) glossaries of terms, (4) camera reviews, (5) files of customer experiences with the cameras, and (6) galleries of pictures taken using the reviewed cameras.

In the case of a product with a rapid rate of technological change, consumers need data in order to determine which attributes are needed for the intended use. There are several ways a consumer could learn which attributes are needed for the type of picture he requires and could judge the performance of cameras with those attributes. He could seek advice from those with prior experience such as a digital camera owner or salesperson. In some cases in a camera store, he can take in-store pictures, although his evaluation would be limited to the LCD screen image. In a book store or library, he could read articles in digital camera magazines or books. Online at a digital camera site, he could peruse the types of data listed above.

The question is how much data should an efficient consumer collect and process. We shall use digital cameras to illustrate our qualitative analysis of this issue. In the case of digital cameras and other products undergoing rapid technological change, we consider the concept of perfect information questionable because acquiring and processing data is a costly activity. We will propose an alternative concept, the information value of data.

2.1 Processing Cost

The first factor limiting data demand is cost. Even without acquisition fees, getting and processing data requires resources. Finding alternatives' specifications, for example, can require examining several brochures or visiting several Internet sites. In addition, if the consumer is faced with new technology or previously unencountered choices, he may have to learn how to interpret the data. Consequently, the cost of data to the consumer should include not only the time and resources spent on acquiring the data, but also the cost or learning how to interpret the data, and the resources spent on interpretation.

We also argue that the Internet processing cost is less than the physical space processing cost for a variety of reasons:

1. **Travel**: It is cheaper to go from site to site in cyberspace than store to store in physical space.

2. **Evaluation**: It is easier to find material on the Internet than it is in physical space. For example, online to find digital camera product reviews, a consumer can go to Google.com and enter the product name with the word "review," to obtain a long list of sites with reviews of the product. This is much more efficient than driving to a local bookstore or library to look through the digital photography magazines in the magazine rack.

3. **Tools**: Cyberspace also dominates physical space in the provision of tools to consumers. Let us consider tables in physical space versus cyberspace. Magazine review articles frequently include tables with a side-by-side comparison of the discussed products attributes, but these tables are fixed. Websites can create personalized attribute tables of only those products that interest the visitor. These tables can also include links to reviews, and current prices. Creating something nearly as useful in physical space would require acquiring and lining up the relevant tables in manufacturers' brochures, which lack a common format.

4. **Price** : It is much easier to perform a price search in cyberspace than in physical space. If a consumer knows what she wants to buy, she can input the product name into a search engine like Froogle.com, PriceGrabber.com, or Dealtime.com. They will return a price distribution of the product prices through linked merchants. With a click, prices of the product including shipping costs can be ordered from lowest to highest. In both cyberspace and physical space a deal can be "too good to be true." For example, in the case of digital cameras, a "too good to be true" price can mean the seller takes the camera out of the box and tries to sell the package components as extras. In cyberspace the customer has a readily available means of measuring the risk, an estimate–frequently given as a number of stars and testimony of previous customers–of the seller's reliability. Thus, a consumer can judge whether a low price is a legitimate offer. Obtaining such information in physical space from a large number of sellers would be prohibitively expensive because of travel costs or time delays in reaching a salesperson by phone and the lack of a readily available seller evaluation procedure.

Nevertheless, even with the aid of computers, more data, even if free, is not necessarily better than less data. Consider how much data could possibly be provided to a consumer in order to evaluate digital cameras. While a consumer has a limited ability to take pictures with a camera before purchase, in some cases a consumer could borrow a camera owned by a friend or look at pictures in the LCD screen of a demo in a digital camera store. A consumer could go to the manufacturer's site to examine the product description and the user's manual. A consumer could read all the reviews in magazines and at digital camera sites to see the results of the each reviewer's tests, which differ among reviewers. This is still only a fraction of the data that could be supplied to the consumer. The potential buyer could be supplied with the detailed specifications of every component of the digital camera, the production details, the research and development reports, and the details of all the testing programs. The consumer could even be supplied with electron microscope pictures of the structure of the sensor. A data file describing the position of molecules on the sensor surface could be obtained. Indeed, the limit of data that could possibly be supplied to a consumer is only set by the Heisenberg uncertainty principle. More data is not necessarily better than less: such a massive data file would be prohibitively expensive to obtain and would overwhelm the consumer's processing capabilities. Indeed, it might well intimidate consumers into making poor decisions. Although a computer-aided consumer can inexpensively process a great deal more data than a consumer without a computer, the amount of data that could be tractably processed is still **miniscule** in comparison to the potential limit.

2.2 Capacity to Discriminate

Another important attribute of data is the capacity to help the consumer discriminate among alternatives' probable performance. Akerlof (1970) was the first to raise this issue in his discussion of the used car market, where buyers were unable to judge the reliability of a used car. Spence (1973) expanded the discussion by highlighting the market incentives of the market participant to provide signals to allow the other party to make a judgement of future performance. A good signal discriminates with low processing cost. In the case of used cars, auto dealers have developed a certification program where used vehicles pass inspections and are backed by warranties. Some of the signals provided by manufacturers include a list of product specifications, such as a list including a digital camera's number of megapixels and size. Third parties also provide market signals. For example, Imaging-resource.com tests the focus time and shutter lag of a digital camera, and DPReview.com makes detailed picture noise measures for dSLR cameras.

In products undergoing rapid technological change, a consumer frequently lacks the knowledge to know which product attributes are needed for the intended product use. To better discriminate he needs knowledge to understand the function of the attributes. For example, in the case of a digital camera, what is the function of an autofocus assist light and under what conditions in photo shooting is it really useful. Part of the data the consumers obtain from friends, salespersons, magazine articles, and online site is knowledge to better understand the attributes of the product line to order to better discriminate.

Once the consumer has found a small set of of digital cameras with the attributes needed for the intended use, he then needs to judge the performance of the cameras within this set. For this purpose, a consumer might use the brand such as Canon as a signal. This signal is not a perfect discriminator because not all Canon cameras are winners. To obtain a better discriminator the consumer might also read several reviews to judge performance or examine the picture and video galleries taken by a particular camera. There is frequently a tradeoff between the processing cost and the discrimination power of data.

2.3 Reliability

The final factor considered in the data's information value is its source's reliability. Second and third parties provide data beyond the consumer's direct sensory interaction with the products. The former - manufacturers and retailers - present data to sell their products, and this data might not be the most useful to enable the consumer to judge among all alternatives in the market. Third-party owners of products, such as friends, relatives, and acquaintances, can provide useful data about a product from their experiences, but they generally know much less about products they didn't buy. Experts who provide product reviews in magazines and websites generally have a conflict of interest. While experts are generally financed by advertising rather than by the prospective buyer, they must provide useful information to attract readers in order to increase their advertising revenue. Thus, consumers are likely to regard expert third-party sources as more reliable for inter-firm product comparisons than a firm comparing its own products with its rivals' products.

The reliability of third party sites depend on how the entrepreneur gets paid for his services. ConsumerReports.org charges the viewer a flat annual fee to access the site while others make money through advertising, sponsorships, and pass through fees. The more independent the site is from the sellers the greater its reliability. If sites that advertise are too critical, they risk losing sponsorships.

2.4 Information Value

The **information value of data** is positively related to its reliability and ability to discriminate among alternatives and inversely related to its processing cost. Let us compare this concept with the standard concept in microeconomic consumer optimization theory that consumers have perfect information that is they are knowledgeable about their alternative so that they select the optimal bundle.

As has been pointed out by Ackerlof (1970) the concept of perfect information is a deficient concept. In response to a costly search in acquiring data, Herbert Simon (1955) proposed the concept of satisficing under which consumers given expensive search costs stop with an alternative that is good, but not the best. Decision psychologists led by Tversky and Kahneman, see Gilovich, Griffin, and Kahneman (2005) for an update, have shown that decision makers use simplifying heuristics to solve decision problems. These simplifying heuristics can lead to good performance, but sometimes lead to errors. Gigerenzer (2001) asserts that decision performance is less than optimal even in the case of costly information.

It is our contention that if a consumer gains access to a data set with higher information value, his performance in terms of finding a preferred item will improve. In a recent experiment Norman et al (2007) asked subjects who regularly used a stick ball point pen to select the preferred pen first without writing with any of the 15 alternatives and second with writing with the pens. 31 out of the 40 subjects selected a different pen as preferred after writing with the set. On average they preferred 3.2 pens to the pen selected without writing. Nevertheless, all but one of the subject considered the pen they selected prior to writing with them as adequate for taking notes, a measure of satisficing. These pens are packaged in plastic containers in in bundles from 10 to 48 so that student can not write with the alternatives before buying a bundle. The search costs of writing with a pen are high. Enabling students to write with pens in stores would improve consumer performance, but would be costly to stores in terms of possible pilfering.

Our research is aimed at investigation providing consumers with data sets with higher information value.

3 Digital Camera Selection Procedures

How do students search for a digital camera? In order to construct a useful survey, we first interviewed 20 students. We then surveyed 27 students in 2003 and 40 students in 2006. Of the last group 23 students were given a follow-up survey. Interviewed students were paid \$10 for the interview. Surveyed students were paid \$5 each and those that participated in the continuation survey an additional \$3. We shall focus on the last two surveys.

Subjects were given a list of possible data sources. For each source, subjects were asked whether they used it and if so, how useful it was where the response "not useful" was recorded as 1, the response "useful" as 2 and the response "very useful." as 3. The results are displayed in the table below:

Data Sources and Their Usefulness

Source	Type	Fraction	Usefulness
People	Friend or Relative	0.73	2.21
People	Sales clerk	0.6	2.30
Website	Manufacturer's Website	0.5	2.14
Text	Photography or PC magazine	0.28	2.5
Text (Website)	Consumer Reports	0.35	2.23
Website	CNET	0.25	2.44
Website	Online Site (See a below)	0.48	2.53

where (a) on the questionnaire "Online Site" was "Online Site such as DCResource.com, DPReview.com, Imaging-Resource.com, and Steves-digicam.com. "Fraction" is the fraction of the 40 subjects who used the indicated data factor. In addition, the fraction of subjects that used either a friend or sales clerk was 0.9 and the fraction that used at least one of the Text or Website sources was 0.75.

Let us consider how the three data properties of processing cost, discrimination, and reliability affected the subjects' search. Let us start with reliability. The subjects used an average of 4.2 sources suggesting the need to double-check the data from any one source and that using more than one data source expanded the data coverage of digital cameras. Also, subjects found the data from 3rd party sites to be more useful than 2nd party sites. For example, the mean of Online Site, which is 2.53, is more than 3.5 standard deviations greater than the mean of Manufacturers Website, which is 2.14.

Now let us consider processing cost. Students searched an average of 9.8 hours over an average of 1.2 months to buy their camera. Search time ranged from 2 to 60 hours. DCResource.com has over 60 camera review of 15 pages or more. If the subject read these reviews at 20 pages an hour he would take 45 hours. But, there are 6 sites with reviews and numerous articles and reviews in magazines and books. Even the subject who searched for 60 hours processed only a small fraction of the available data, which as we pointed out is a miniscule fraction of what could be provided.

To reduce their processing costs, subjects generally select a small set of cameras using the criteria listed below, and then evaluate this small set much more carefully. In the second survey when asked, "Consumer search procedures vary widely in buying digital cameras. Many consumers first choose a small set of cameras that they evaluate closely to determine the final selection. <u>How many cameras did you</u> <u>evaluate closely?</u> *(For example, evaluating closely might mean you examined the camera physically, read a review, took or looked at pictures - several minutes in each activity).*" One subject responded with "1"; twenty-five subjects responded with "2 or 3"; thirteen subjects responded with "4 to 6"; and, one subject responded with "more than 6."

Now let us consider the property of discrimination. In the market there are currently over 150 new digital camera models. How did consumers reduce this number to the number they listed above? In the continuation survey, subjects were asked to rank the following attributes in the order that they applied them to their decision:

Factors: Importance and Order		
Factor	Importance	Order
Size (Tiny, Small, Large)	1	1
Type (point and click, small with manual controls, Telephoto, prosumer, dSLR)	6	5
Megapixel (2,3,4, 5 and so on)	2	2
Brand (Canon, Nikon, Sony and so on)	4	4
Special feature (Optical zoom, autofocus assist light, great video. Any special feature that camera must have such as external flash)	5	6
Budget (price must be less than budget)	3	3
Style (Must be a fashion statement)	7	7

where importance and order are the ordinal rankings of the averages. The inconsistencies can be attributed to allowing the subjects to list factors as ties. The top four were size, megapixel, budget, and brand.

There are a variety of ways students chose the small set that they closely evaluated. What is important to note is that specifying a size, megapixels, budget, and brand can define a small set. For example, a tiny Canon with 4 or 5 megapixels costing less than $350 gives you a small set.

The response to the question,"**How did you judge the quality of the digital camera you purchased?**" is shown in the table below:

Factors to determine the quality		
Factor	Fraction	Usefulness
Selected most megapixels for budget as measure of quality	0.85	2.21
Took the advice of a roommate, friend, relative on quality of camera	0.53	2.14
Took the advice of a sales person on quality of camera	0.52	2.29
Choose a particular brand based on reputation, for example Canon or Nikon	0.8	2.38
Read review(s) of particular cameras either in magazine or online	0.63	2.6
Determined quality of pictures by looking at the LCD viewfinder pictures	0.4	2.1
Examined galleries of pictures and determined the quality of pictures yourself	0.38	2.47

Fraction and Usefulness are defined in the same way as in the first table in this section. In order to interpret the table it is first noted that on average the subjects considered used 4.7 factors to judge the quality of their cameras. The most useful factor was magazine or online reviews with a mean of 2.6. Consider that nonzero responses of the subjects. If we consider pairwise the difference between the mean of reviews with the mean of the other factors divided be the largest standard deviation of the two, the usefulness of the reviews is more than 3 standard deviations better than most megapixels, advice of friend, and LCD monitor. It is more than 2.5 standard deviations better than advice of a sales person and more than 1.9 standard deviations better than brand.

4 Improving Consumer Selection Procedures

In measuring trends in leisure from 1965 to 2003, Aguiar and Hurst (2007) showed that men during this time period have decreased their time devoted to obtaining goods and services from an average of 4.85 to 4.34 hours per week and women during the same time frame have decreased their time spent for this activity from an average of 7.33 to 5.93 hours per week. At the same time with the shift from mass to niche marketing and rapid technological change, the choice problem of large numbers of alternatives and products with new features or completely new products has become more difficult to solve. In the US the problem is exacerbated by the decline in retail salespeoples knowledge as retailers reduce incentives towards knowledge, such as commissions and shift to hiring part-time workers to reduce fringe benefits.

The one improvement in consumer search capabilities is the development of second and third party sites on the Internet. A jdpower.com news release of 25 October 2007 reports that 23 percent of used car buyers now use the Internet to search for their vehicles, a 44 percent increase over 2006. A J. D. Powers 2006 study (2006) reports that 66.6 percent of new car buyers perform auto research online and of these online researchers 77 percent go to third party sites. In electronics there has been a growth of third party Internet sites such as CNET.com. In the area of digital cameras several sites that are previously mentioned have emerged. DCResource.com, which was founded in November

1997, now reports receiving over 800,000 unique hits per month in 2007. A 23 Oct 2006 press release at ce.com reports a study by Yahoo and the Consumer Electronics Association that claims that over three-fourths of consumer electronic product sales are influenced by Internet research. We argue that the consumer data structure is undergoing a transformation as more consumers do research online.

One aspect that third party Internet data providers could improve is software decision aids. Online sites can improve their product selection codes. Our survey indicates that only 9 out of 40 students who bought a digital camera used a selection code, which suggests that consumers are not aware of these codes or if they are, they do not consider them worth using. Our survey of digital camera sites revealed few examples of digital selection code.

There are two areas that a selection code for digital cameras can be useful. The first is in the second step of the selection process: finding a small set of cameras with the attributes to take good pictures for the intended use. In digital cameras there are a large number of details about the attributes that a consumer must master if his decision can be said to have been made with perfect information. For example, DPReview.com, a site for serious enthusiasts, lists over 90 attributes of each camera listed while DCResource lists about 30. Our survey showed over half of digital camera buyers were overwhelmed by the number of details. Moreover, asking a friend for advice is not always wise. We also gave the subjects a short quiz about digital cameras and found the average score was 6.7 out of 10. This indicates that even after doing their research to buy a digital camera, subjects were not very knowledgeable. As we shall discuss later, salespersons can have perverse incentives.

Given the time that a consumer has to spend on her search, she can fail to understand the importance of desirable features. Let us consider an auto focus assist light (AFAL), that enables a digital camera to focus quickly and accurately in dim light. Jeff Keller has frequently argued in his review that all digital cameras should have an auto focus assist light, as even a camera for a family of four is likely to encounter photo situations where it is useful. College students who frequent clubs or parties definitely have a need for an AFAL. We found 6 students who did not buy a camera with this feature and took pictures in low light conditions. The 5 coeds who bought a Casio EX Z3 said that on average 86% of these shots turned out with poorer quality than desired. The coed who bought a newer Olympus FE 190 said that 15% of these shots were poorer than desired. The coeds would have been prepared to spend an additional \$30, \$37, \$50, \$50, \$100, and \$250 in order to have obtained a camera with this feature. Subsequently, the coeds who bought the Casio EX Z3, bought digital cameras with an auto focus assist light. If a consumer buys a telephoto camera to take pictures of wildlife including deer at sunset, he would obtain a less than optimal camera if he failed to consider a camera that incorporated a lens stabilization system that reduces shaking at low light.

The second aspect of a digital selection code is providing consumers better evaluation techniques for the final selection. As the research initiated by Tversky and Kahneman shows, humans use simple heuristics to make decisions. Let us consider three such heuristics. The first is judging the quality of the picture by looking at the picture in the LCD screen. The number of pixels in LCD screens is in the hundreds of thousands and the number used by some firms is one half that used by others. The quality of the picture on the LCD screen is a function of the number of pixels used in the screen and this quality may not be a great indicator of picture quality of the corresponding picture on the memory card.

A second heuristic that is a questionable discriminator for quality is using the number of megapixels as a discriminator for quality. The number of pixels in a square inch of picture increases by the square root of the number of pixels, so this heuristic is a gauge of the amount of detail in a picture. But a reading of the reviews over several years at DCResource would inform the reader that the digital camera firms have been engaged in an "arms race" to increase the number of megapixels in the CCD sensor. When the firms first come out with a digital camera at the new megapixel frontier, the problem to overcome is picture noise. After a few generations at the frontier the noise problem is overcome and the firms increase the number of megapixels once again. The quality of a picture depends on other factors such as the algorithm to process the sensor data and the quality of the camera lens. One student who bought a digital camera from a firm leaving the digital camera business at Overstock.com using the maximum megapixels for his budget suffered deep regret when he realized that if he dropped down one megapixel, he could have bought a much better camera. A third heuristic is using brand as a discriminator of quality. As was previously pointed out, while Canon makes many quality cameras, their cameras are always better than those of their competitors.

A faster way to educate consumers concerning desirable camera features and providing them with better discriminators of quality has positive value.

5 Selection Code Development

In our digital camera selection code the decision process is divided into two components. The first stage is to select a small set of quality cameras within budget with the attributes to take good pictures in the intended photographic conditions. Because consumers are not well informed about digital camera attributes, there is an education module to improve their selection process at this stage. The second component of the decision process is to send the user to online digital camera sites where they can read the reviews and examine photo galleries of the small set selected in the first stage in order to determine the preferred item.

The educational component was the most challenging to develop. To help consumers make better choices a fundamental question is how much data to incorporate into the educational component. Again, the greater the detail the greater the processing cost for a consumer to master the material. Because our subjects demonstrated little knowledge about digital cameras, our first code, developed in 2004, provided the user with explanations for less than half the detail considered by DPReview.com, the most technologically advanced site. Explanations of each incorporated feature were at least two levels deep: the first was a brief overview, and the other levels provided much greater detail. The code taught the consumer which features were needed for different types of shots. The module also gave them an estimate as to how long it would take them to learn how to use various features such as shutter control. It provided tests the user could perform to decide what size of camera best suited them and the details about megapixel and sensors. There was an online questionnaire that when filled out gave the user a list of "essential" and "desirable" features for taking the user's desired pictures. The education function consisted of over 40 html pages that test subjects could not be master in an hour, but could master if given a week. The code can be found at http://www.eco.utexas.edu/Homepages/Faculty/Norman/000Cam.

We then refined our code with the goal of subject mastery of the first decision process in 20 minutes. We did so by integrating the education program with the decision structure. The new decision structure began with a decision whether to pick a small or large camera. Subjects were given the tradeoffs between the two groups: small cameras are easier to carry around, but lack the features and picture quality of large cameras. To clarify the difference between the two groups, we provided pictures to illustrate why the external flash hotshoe of a large camera is necessary to take pictures of large groups in dimly lit large spaces. We also explained the concept of optical zoom noting that large cameras have greater optical zoom, and explained why dSLRs are necessary for indoor sports shots.

If the user clicked on large camera, the viewer was provided with a page of pros and cons to decide among a telephoto, a prosumer, or a dSLR digital camera. If they chose the dSLR option, we assumed had some camera knowledge and we provided them with a table of links to reviews of the dSLR cameras. If the subject selected telephoto, prosumer, or originally chose small camera, the next page educated the subject about digital camera attributes. We shall focus of the small camera page as the telephoto and prosumer pages are similar. To accomplish the 20 minutes goal, we aggregated the number of defined attributes for a small or tiny camera to ten features: "Best Camera List,"; auto focus assist light, video quality, manual controls, capture the moment, ease of use, camera size, lens, megapixels; and price. A camera on a "Best Camera List" meant that at least one reviewer thought the camera was superior. For nine of the attributes we provided a one sentence explanation and a "More Info" button. For example, the short explanation of the auto focus assist light was "An auto focus assist light, afal, enables a camera to focus properly in dim light." The "More Info" explanation is "**An auto focus light is highly recommended for taking pictures in low light conditions, such as those at parties for young adults.** Without an auto focus assist light, your camera is likely to have difficulty focusing in such conditions. Remember if you want to take pictures of large groups in low light, you also need an external flash. While some small cameras have slave external flashes for mid sized groups, better external flashes are found on Large prosumer and dSLR. " The first sentence was in bold red letters for emphasis. The short explanation for the other attribute, camera size, was "**Play DEMO video, a must see =>**" in bold red letters. If the subject responded, she viewed a short video that demonstrated the difference between small and tiny cameras.

Two attributes that need an explanation to understand the experiment are video quality and capture the moment. We pointed out that video quality on digital cameras in terms of picture size and frames per second has been improving over time and that the best was a picture size of 640 x 480 pixels and 30 frames per second. To capture the moment, you need a short shutter lag. The shutter lag on digital cameras has been decreasing over time and at the time of the experiment 0.1 or less seconds was considered quick. The ten attributes aimed to provide as much discrimination among alternatives as possible. For example, the attribute "Manual Controls" divided cameras into those that did and did not have aperture and shutter priority. The former generally have a complete set of controls, while the latter are point-and-click cameras. For subjects without much digital camera knowledge, this easily understood distinction provides reasonable discrimination capacity.

The next page is a set-selection-by-aspects decision rule, Norman et al (2004). There are so many new digital cameras on the marketplace that a user can specify the characteristics determined by the intended use such as size and features to obtain a much smaller set for detailed study. On the first six attributes we listed the user was given the choice of "Yes" or "Doesn't Matter." For the others the user had a small number of choices. For example, for price the user chose among "Price no more than \$200, \$300 , \$400 , Doesn't matter." Below the attribute table we had a box listing the number of cameras with the selected criteria. Initially the number of small cameras was 129 and is reduced by each selection of a new criteria. If the number falls to 0 the user is recommended to relax some of the criteria. Because the code works quickly the user can play "what if" scenarios to determine tradeoffs. Once the user has a manageable list, she can click on a button at the bottom to obtain this list of cameras in a table giving their features.

The first stage is to create a small list of digital cameras with the required attributes to take the intended pictures. The reason for obtaining a small list of digital cameras at this stage is that the second stage involved labor intensive operations such as reading reviews and examining picture galleries. To reduce a larger list to a smaller one the attributes included one quality discriminator on a "Best camera list" meaning a 3rd party reviewer recommended the camera. This discriminator was considered superior to the heuristics of brand, more megapixels is better, or the quality of pictures in the LCD screen. Quality of pictures is one aspect of being placed on such a list so that a camera on such a list with the specified attributes is also likely to take superior pictures.

The final page gives the user alternative approaches to selecting the final choice such as reading camera reviews and examining picture galleries that are attached to review, the alternatives considered most useful in our survey. The user can decide how much time to spend depending on how much detail he wishes to consider. The reader wishing to examine the Oct 2005 version of this code can go to http://www.eco.utexas.edu/Homepages/Faculty/Norman/01Cam/final.html.

We chose this decision procedure over a code with a compensatory decision rule with sliding scales (for example, see http://www.myproductadvisor.com/mpa/camera/inputSummary.do) for each attribute where the value chosen on each sliding scale indicates the importance of that attribute. This approach assumes that users that have little knowledge about cameras have formed preferences over the attributes. Also, how the code weighs the sliding scales to obtain the outcome is not readily apparent to the user. Thus, to obtain a set of cameras with the attributes needed for a particular type of picture can be a difficult task.

6 Experiment

We devised an ANOVA experiment with the Duncan test to evaluate the performance of our code in determining a small set of quality digital cameras for three sets of pictures, the first decision process. We compared our code with (1) asking the advice of a digital camera sales clerk, (2) asking the advice of a digital camera owner, (3) having access to the internet, but not our code.

It should be emphasized that the experiment focuses on the first stage of the decision process and does not involve the more labor intensive second stage process of reading reviews, examining digital camera photo galleries, or physically interacting with the cameras in a store. The question is whether the subjects select a small set of quality cameras with the attributes to take good pictures under the stated scenario. Sales clerks were selected to compare their knowledge of digital cameras. From our surveys we found that students frequently ask the advice of a roommate who owns a digital camera, hence subjects who owned a digital camera were selected. As will be discussed, we tested a previous version of our code against an online selection code lacking an education module. This time we had one group of subjects just with access to the Internet.

The subjects were asked to find three quality cameras for each of the following scenarios:

1. A soccer mom has a budget of $300 and wants a camera that fits in her medium sized purse to take pictures of her children in outdoor sports, flowers in her garden and small groups of people outdoors and indoors under artificial light. She wants a camera that will allow her to take the best pictures possible for her budget and she has the time to learn how to use all the features of her camera.

2. A student who has a budget of $550 wants a camera to take great pictures of birds outdoors both still and flying. Sometimes in the evening before sunset. The student also wants great pictures of UT football games from seats in the upper deck.

3. if female answer a and if male answer b

   a. A female student with a budget of $300 wants a camera to fit in her small date purse to take pictures and small videos of small groups of friends at clubs on 6th street at night.

   b. A male student with a budget of $300 wants a camera to fit in his shirt pocket without showing to take pictures and small videos of small groups of friends at clubs on 6th street at night.

For the experiment there were 52 subjects, evenly divided into four groups. Each had the following resources:

1. Students with our code. The experiment version of code to be found at http://www.eco.utexas.edu/Homepages/Faculty/Norman/00Cam. The instructions for the second decision stage were removed because the experiment was over the first stage decision process.

2. Students who had access to the Internet, but did not have access to our code

3. Students who owned a digital camera. Students who own digital cameras frequently do not know the model number of their own camera let alone others. In order to get these students to specify the brand and model number, they were given pictures of the various cameras with the name and model number, but no additional data.

4. Salespeople in stores selling digital cameras. Students and the first author memorized each scenario, went to each store, and acted as consumers, orally requesting the sales clerk's recommendation.

The first three groups had the following instructions: Objective: You are to use the software package to find 9 digital cameras: 3 for each of 3 specifications of the type of pictures they should excel. In each category rank the cameras 1, 2, and 3.

1. Find the best cameras that can take the indicated type of pictures for the price. For each situation there are certain features the camera must have. What are these features? **Do not add features that you might personally like in a camera!!!**

2. Take the price of the camera in the data as given. **Do not try to find a better price.**

3. Evaluation criteria: Do the cameras you recommended have the required features? **To earn points you must list the brand and model number of each camera you list. There are up to 5 points per camera.**

For the sales persons we were interested in what advice they would give to customers so we pretended to be customers. We went into a store in a group of three. The first member of the group verbally gave the sales person a scenario and asked for three recommendations. After obtaining the recommendations, the next person repeated the process with the next scenario.

The first three groups were given one and a quarter hours to answer a quiz and finish their task. Their incentives were a flat fee of $10 and chance to win an additional prize: $100 for best performance, \$50 for 2^{nd}, or \$20 for 3^{rd}, and \$10 for each of the three next best performers, and \$5 for each of the four next best performers after that. Each of the four groups had \$220 in prize money and an expected earnings of \$27. Because we wanted to see how salespeople would respond to their store incentives, we did not offer this group any additional incentive, nor did we give them a time limit.

The subjects scored 1 point each for most of the correct attribute selected – a few attributes required a scale. The scoring is shown in the following table:

Criteria	Scenario 1	Scenario 2	Scenario 3
auto focus assist light	N/A	N/A	1
best video	N/A	N/A	1
manual controls	1	1	N/A
on "Best Camera List"	1	1	1
price less than budget	1	See a below	1
quick when prefocused	1	1	N/A
small size	1	N/A	1
stabilized lens	N/A	1	N/A
tiny size	N/A	N/A	1
zoom	See b below	See c below	N/A

Where a means 1 if less than budget, -1 or -2 if more than \$200 or \$1000 over budget, respectively

b means 0.5 if 2x, 1 if 3 x, 1.5 if 4-9x and 2 if 10x

c means 1 if zoom $>$ 4x and 2 if zoom $>$ 10x

The scores were normalized on a 0 - 10 scale. The term "best video" means a picture size of 640 $\times$ 480 and 30 frames/second. This was the best video in a digital camera at the time of the experiment. The term "on 'Best Camera List"' means one of the sites that the user would be sent to for the stage two selection process had the camera on a recommended list. This criteria for quality was considered better than using brand name such as Canon. In the stage two selection process consumers would read reviews and examine photo galleries. The term "quick when prefocused" refers to the shutter lag. The first digital cameras had a long shutter lag making it difficult to capture the moment in sports or children photography. Over time the shutter lag has decreased with technological advance.

A camera in the experiment was considered quick if the shutter lag was less than or equal 0.1 second. The ANOVA results for four groups, three scenarios, and fifty-two subjects with three observations each are:

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	2093.0	190.3	11.56	<.0001
Error	144	2369.8	16.5		
Corrected Total	155	4462.8			

The Duncan test with an α of 0.05 grouped the performance of the 4 groups into three groups, A, B, and C as follows:

Grouping	Mean	N	Subjects
A	27.2	39	Our Code
B	22.5	39	Sales Clerks
BC	21.3	39	Own Digital Camera
C	19.9	39	Access to Web

Our code was statistically superior and the Duncan test indicated the differences among the four groups were statistically significant. We tested minor changes in the scoring and determined that small changes considered in the scoring resulted in a variation of F value from 9.04 to 11.56. In each of these variations the performance order of the four groups was the same and the Our Code group was significantly better. In some cases, the performance of the Sales Clerks group was not statistically superior to the Own Digital Camera group, and in some cases the performance of the Own Digital Camera group was not significantly better than the performance of the Access to Web group. Also, in an earlier experiment we found that our code was statistically superior to the sliding scale code created by myproductadvisor.com, see Norman et al (2005). Our assessment was that the sliding scale code did not provide the user with any education so subjects did not know what features were needed for each scenario. The codes at the other sites mentioned also did not have an education module, so were not considered worth testing.

It required several years of effort to create a code that was statistically better than sales people. This fourth version of the code is the first that produced statistically superior performance over sales people. Why did our code perform better than the other groups? The fact that the subjects with our code had access to on "Best Camera List" was not a deciding factor. If the on "Best Camera List" is dropped as a criteria, the F test value drops from 11.56 to 10.54 and the Duncan test of the groups remains the same. Our subjects did not always select cameras on a "Best Camera List" and if subjects choose major brands they were frequently on a "Best Camera List."

The difficulty is how to educate subjects quickly to make good decisions. The major improvement over the previous version of the code was incorporating the video that made the difference between a tiny and small camera clear. The effect of this video is seen when we consider the three scenarios separately, which have a smaller sample size and more variation in the F values for the cases considered. We considered four cases of the third scenario, and the corresponding the F tests ranged from 12.97 to 18.82. In all four cases the Duncan test revealed that our code group placed first, the subjects who owned a camera placed second, and the other two groups were not significantly different. The video communicated so that all our subjects chose a tiny camera. The sales persons recommended a tiny camera less than subjects who owned a digital camera. It is possible that if we had given the sales people the same instructions as the other three groups, their performance would have been better, but this would have negated our effort to solicit their advice as customers.

On the second scenario the four F test values ranged from 8.77 to 10.49. In all cases the sales persons placed first and subjects who used our code placed second. The difference was not statistically significant. This is one area where performance decreased with the fourth version of the code versus the third. In the third version of the code there was no initial decision between large and small cameras. Also in the current version of the code, the html page that showed the relationship between focal length (optical zoom) and magnification was too technical. A simpler, more dramatic explanation probably would have produced better results. In the first scenario the four F test values ranged from 5.58 to 9.04. In three cases, the Duncan test revealed that group that used our code had statistically superior performance.

As our surveys showed subjects who owned a digital camera were not well informed about digital cameras. Subjects who just had access to the Internet had a data source that involved large processing costs. The performance of sales persons was a surprise. The part-time sales persons at Circuit City and other electronic stores generally did better than sale persons at specialized camera stores. We found out that the latter sales persons had questionable incentives. They always recommended a camera well below budget so that they could sell add-on services such as an extended warranty. For example, with a budget of \$400, a sales person recommended a \$330 camera and strongly advised a \$130 three-year extended warranty with the purchase. In addition, their recommendations were influenced by the variations in manufacturers incentives. We were genuinely surprised by their recommendations in the third scenario.

7 Conclusion

The surveyed students took an average of 9.8 hours to find a digital camera. Assuming our code would reduce the search time to four hours and that the subjects valued their time at \$8 an hour, the value of such a code would be about \$40 per subject.

We believe that the future of third party Internet sites will be in creating selection software that will become increasingly sophisticated artificial intelligence programs. The development of such codes can move consumer performance closer to the ideal of "perfect information."

References

1. Aguilar, M. and E Hurst, (2007), Measuring Trends In Leisure: The Allocation of Time Over Five Decades, *Quarterly Journal of Economics*, August, 969-1006

2. Akerlof G. , The Market for "LEMONS": Quality Uncertainty and the Market Mechanism,(1970), *Quarterly Journal of Economics*, Vol. 89, 488-500

3. Gigerenzer, G, (2001), The Adaptive Toolbox, in Gigerenzer, G, and R. Selton (eds), Bounded Rationality: The Adaptive Toolbox, MIT Press, Cambridge, MA, 37-50

4. Gilovich, T., D. Griffin, and D. Kahneman (ed), (2005), Cambridge University Press: New York

5. Norman, A., K. Brehm, C. Hinchey, S Kejriwal, K. Kuang, S. Ler, K. Powers, A. Robertson, J. Schieck, and J. Sussman, Sequential Consumer Model, paper presented at the fall 2007 Economic Science Conference in Tucson, AZ

6. Norman A, M. Aberty, M. DeGroot, S. Gour, C. Govil, J. Hart, G. El Kadiri, S. Keyburn, M. Kulkarni, N. Mehta, J. Sanghai, V. Shah, J. Schieck, Y. Sivakumaran, J. Sussman, C. Tillmanns, K. Yan, and F. Zahradnic, The Procedural Consumer: The Polynomial Assist, paper presented at the Jun 2005 ESA conference in Montreal, Canada. All Norman et al papers are available in pdf form at http://www.eco.utexas.edu/Homepages/Faculty/Norman/research.htm

7. Norman A, A. Ahmed, J. Chou, A. Dalal, K. Fortson, M. Jindal, C. Kurz, H. Lee, K. Payne, R. Rando, K. Sheppard, E. Sublett, and I. White, (2004), On the Computational Complexity of Consumer Decision Rules, *Computational Economics*, 23(2), 173-192

8. Norman, A., A. Ahmed, J. Chou, K. Fortson, C. Kurz, H. Lee, L. Linden, K. Meythaler, R. Rando, K. Sheppard, N. Tantzen, I. White and M. Ziegler, (2003), An Ordering Experiment, *Journal of Economic Behavior and Organization*, Vol 50 249-262

9. Norman A, J Chou, M Chowdhury, A Dalal, K Fortson, M. Jindal, K. Payne, and M Rajan,(2001), Two-Stage Budgeting: A difficult problem, *Computational Economics*, 18 259-271

10. Payne, (1976), Task complexity and contingent processing ion decision making: An informational search and protocol analysis, *Organizational Behavior and Human Performance*,16,

366-387

11. Simon, H. A. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*,. 69: 174-183

12. Spense M. , Job Market Signaling, *Quarterly Journal of Economics* 87 (3) (1973) 355-374