Chapter I
Comparison-Shopping Services and Agent Design:
An Overview

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ABSTRACT

This chapter provides an overview of comparison-shopping services. Four research topics are covered: How to design a good shopbot? How Shoppers using the comparison-shopping services? What is the strategic use of comparison-shopping as a new channel by online vendors? And what is the impact of comparison-shopping on existing price equilibrium and electronic market structures? Emerging research topics like mobile comparison as well as comparison in health information are also discussed.

INTRODUCTION

Comparison-shopping was introduced into the World Wide Web in 1995 as the third mode of B2C ecommerce after online retailing and online auction. Shopbots became a popular shopping aid. They evolved from providing mere price information to offering a combination of product and vendor review as well as ratings for functions for a particular product or service. The vendor attitude towards comparison-shopping also evolved from doubt and refusal to complete acceptance and paying to participate.

Daily life is also influenced by this service. More and more people visit one of the major comparison-shopping sites before make any important purchase online. Cell phone users found they could be informed about online prices for the same product while they are shopping in a local store, and all they needed to do was to key in the barcode.

The concept of Web-based comparison-shopping was extended into the public domain too. Several state governments set up comparison-shopping websites to allow their residents to compare the service quality of hospitals and physicians as well as prescription drugs.

Web-based comparison-shopping seems also to have increased the general welfare of the society. We found term life insurance rates dropped around 8 to 15 percent because of the use of comparison-shopping sites.

The research in the field of comparison-shopping, however, is relatively scant. This book aims at providing a summary and general reference for existing research in this field.

WHAT ARE COMPARISON-SHOPPING SERVICES AND SHOPBOTS?

Comparison-shopping services refer to the Web-based service online shoppers use when they try to find product, price, and other related information aggregated from multiple vendor sites. Instead of visiting each vendor site offering the same product, online shoppers can view the prices from the comparison-shopping site and make shopping decisions. Once they made the decision, they will be redirected to the chosen vendor site to complete the purchase.

Shopbots is a term that refers to the software agent on the backend of the comparison-shopping service. Though there are variations in design and implementation for different services, shopping basic functions include data collection, storage, and presentation. It is the data collection methodology that differentiates most shopbot technologies, which could roughly be divided into two categories: data wrapping and data feeding.

Shopping.com is a typical comparison-shopping service. A shopper may use a keyword to locate a product or browse to find a product from existing categories. Once a product has been identified, the shopbot displays the prices from multiple vendors. In addition to prices, it also provides product review and vendor rating information to the shopper. On the back end, a sophisticated shopbot technology was used to allow vendors to feed their product price information into the Shopping.com database. Meanwhile, these data are matched with product review and other cost information to be presented to shoppers upon request.

Shopping.com is only one example of comparison-shopping services. In other business categories like online travelling, comparison-shopping had already been the preferred business approach, even before the Web era, and their transformation to the Web was more challenged by existing business model than by technology.

Consider the so called "big three" in online travelling: Expedia.com, Travelocity.com, and Orbitz.com. All of them offer one-stop comparison-shopping for integrated services, including airfare, hotel, and car rental. Because of the maturity of such business categories, derived comparison-shopping services like Kayak.com also emerged to allow shoppers to compare offers provided by different comparison-shopping services. In personal finance, comparison-shopping services like bankrate.com allow individuals to find the best loan rate offered by different financial institutions for their mortgage and other financial needs.

Apart from pure online comparison-shopping services, in recent years, mobile comparison-shopping services have also emerged and have been adopted gradually. All these innovations have important implications for the future evolution of comparison-shopping services.

Compared with the explosive growth of comparison-shopping services and shopbots, research in this field is relatively limited. We classify the existing research in this field into following topics:

1. **Agent design:** How to design a good shopbot?
2. **User:** How shoppers use the comparison-shopping services?
3. **Vendor:** How online vendor use comparison-shopping strategically as a new channel?

4. **Impact:** What impact comparison-shopping has on existing price equilibrium and electronic market structures?

Next, we first briefly illustrate the evolution of comparison-shopping services and then give a brief account for each above research topic.

A SHORT HISTORY OF COMPARISON-SHOPPING

The Emergence of Comparison-Shopping Services

Though it is widely believed that the BargainFinder experiment in 1995 was the first shopbot in the public domain, at least two successful comparison-shopping services preceded or went online at about the same time as the BargainFinder experiment: Killerapp.com and Pricewatch.com.

Motivated by finding the best price for computer accessories, Ben Chiu, a young Taiwanese immigrant to Canada, developed Killerapp.com to allow shoppers to find the price of a computer part from his website. The prices data were initially collected manually from computer-related trade journals and catalogs. Later, as a gifted programmer, Chiu coded a shopbot to collect price data from online vendors directly. Killerapp.com became a hit in 1997 and then was sold to CNET and integrated into its CNET shopper system in 1999.

During the same time period, a similar comparison-shopping service, Pricewatch.com, was also launched by a San Antonio entrepreneur, though it used a different approach to get the price data: instead of searching vendor sites or getting prices from magazines, it asked interested vendors to register with Pricewatch.com and then provide price data to the service.

The aforementioned two comparison-shopping services soon became established but received relatively little public attention and media exposure compared with the BargainFinder experiment.

BargainFinder was an agent designed for a phenomenal experiment conducted by then Andersen Consulting and Smart Store Research center in 1995. The intent of this experiment was not to test how an effective comparison-shopping service could assist consumers in online shopping; Instead, it was designed to test the impact on online vendors of the price arbitrage behavior of online shoppers.

When electronic commerce was in its infant age in 1995, online vendors doubted the Return on Investment or ROI of providing a premium site with rich product information. It was argued that online shoppers might take advantage of the rich product information provided by premium sites like Amazon and then purchase the actual product from another online vendor charging a lower price. This behavior may lead to a situation called Cournot equilibrium (Cournot, 1838), in which online vendors compete solely on price and compromised the online shopping experience, a ruinous outcome for both online retailers and consumers. The emergence of comparison-shopping services might aggravate the situation. Thus, to test the reactions of consumers and online vendors when such technology was available, BargainFinder was built and deployed on the Web for public trial.

The basic interaction mode between BargainFinder and online shoppers defined the style for all subsequent comparison-shopping agents:

"[BargainFinder] takes the name of a particular record album, searches for it at nine Internet stores, and returns to the user a list of the prices found. After the search, the user can select one of the stores and be taken electronically into it and directly to the album. He then has the option of getting more information, looking for other albums, or buying the product" (Krulwich, 1996).

It turns out that even though BargainFinder was a very primitive agent, most online shoppers would like to use it at least occasionally, according to the survey conducted during the experiment by the research team. Also, as expected, 90% BargainFinder users clicked on the cheapest price in the list.

The responses from online retailers diversified. Some refused to be contacted by the team or even blocked BargainFinder's access while others sought collaboration with BargainFinder and hoped the agent could search their sites too.

The initial reactions of both online shoppers and online retailers represented typical behaviors later experienced by subsequent comparison-shopping services. Though lasting only a short time, the BargainFinder experiment provided valuable information about the early attitudes of online shoppers and vendors when faced with the convenience (for shoppers) and challenges (for vendors) brought by comparison-shopping services.

Early Services and Shopbots

The popularity of the BargainFinder experiment motivated many techno-entrepreneurs. Hence, a large number of more sophisticated services emerged between 1996 and 1998. Some notable ones included Pricescan, Jango, Junglee, ComparisonNet, and mySimon.

Pricescan.com was launched in 1997. Like BargainFinder, Pricescan can search and aggregate price information from multiple online retailers for computer products. It could also provide nifty features like displaying high, low, and average price trends over the past several weeks for each product. Pricescan.com emphasized its pro-consumer position in providing price comparison information. According to David Cost, its co-founder, Pricescan did not charge online retailers to be listed in its database. In addition, to bring consumers the best prices, it obtained pricing information not only from vendor web sites, but also from off-line sources like magazine ads. Pricescan.com survives through the revenue generated from the banner advertisements on its website.

Jango.com or NETBot was based on the prototype of a comparison-shopping agent designed by three researchers at University of Washington (Doorenbos, Etzioni, & Weld, 1997). A notable feature of Jango was that it could automate the building of a wrapper for a specific online vendor. Like BargainFinder, Jango was a research project-like agent and it was soon acquired by Excite for $35 million in stock in October 1997.

Junglee was the nickname of a comparison-shopping technology called virtual database (VDB) created in 1996 by three Stanford graduate students. The core of Junglee is an improved wrapper technique that made it easier to search for complex product information online (Gupta, 1998). Instead of having its own Web presence, Junglee.com provides search service to multiple online portals like Yahoo.com. Junglee.com was acquired by Amazon.com for $230 million in 1998.

CompareNet.com was founded by Trevor Traina and John Dunning in 1996 and backed by venture capitals like Media Technology and Intel. It provided comparison information on rather diverse categories like electronics, home office equipment, home appliances, automobiles, motorcycles, sporting goods, and software and computer peripherals. It was acquired by Microsoft in 1999.

MySimon.com was founded in 1998. It used its own proprietary wrapper technology ("Virtual Agent") to collect information from almost every online store. MySimon.com was noted for its easy-to-use interface and was acquired by CNET in 2000. Though being acquired, the brand name was kept and the service remained independent. It has became one of today's remaining major comparison-shopping agents.

As indicated above, from 1996 to 1998, we experienced the first booming of comparison-shopping services in the commodity market and they were characterized by innovative data wrapping technologies. However, many of them were subsequently acquired by major Web portals. Meanwhile, according to one estimation (Baumohl, 2000), there were only about 4 million online shoppers who used comparison-shopping agents in October 2000, less than 1% of the Internet users in the United States at that time. Thus, it was not a coincidence that few of the comparison-shopping services could take hold by amassing a large enough online shopper base.

The Service Became Established

By the end of 1999, the first boom of comparison-shopping agents came to its end due to acquisitions by established ecommerce portals. Another dampening factor was that many ecommerce portals could not strategically synthesize these technologies into their existing infrastructure. As a result, many excellent technologies and burgeoning brand names were abandoned and became obsolete. The acquisition of Junglee by Amazon was one example. The crumbling of Excite@Home in 2001 also ended the further development of Jango.com.

Thus, the comparison-shopping category in the B2C ecommerce market experienced its first reshuffling from 1999 to 2001. Meanwhile, the second generation of comparison-shopping services emerged with an emphasis on improved business models and alternative information retrieval technologies, the data feeding.

Since 2000, a new generation of comparison-shopping services has emerged and has become increasingly popular. If technical innovation characterized the first generation shopbots, business model innovation distinguished the second generation services. The top three are shopping.com (renamed from dealtime.com), PriceGrabber.com, and Shopzilla.com.

Shopping.com was founded in 1997 with Dealtime.com as its name. Together with CNET Networks' mySimon.com, Shopping.com was among the first group of comparison-shopping service to use intensive marketing efforts to build the concept of Web-based comparison-shopping among consumers (White, 2000). With only three years development, Shopping.com managed to rank fourth (behind eBay, Amazon and Yahoo Shopping) among U.S. multi-category e-commerce sites in terms of unique monthly visitors.

PriceGrabber.com was another major comparison-shopping agent that emerged in 1999. It improved its service by incorporating tax and shipping costs into the price comparison as well as the availability of the product from vendors, though this innovation was soon emulated by other services.

Shopzilla.com was transformed from Bizrate.com in 2004. Bizrate.com was an online vendor rating service launched in 1996. Like other first generation ecommerce startups, Bizrate.com found the comparison-shopping service an attractive category and thus made a natural transformation to comparison-shopping since it already possessed an important element, the rating on online vendors.

Sensing the challenges from new startups and observing the opportunities of exponential growth in traffic, established online portals also began to add or transform their shopping channel into a comparison-shopping mode. By 2004, we found comparison-shopping services like Froogle by Google, Yahoo! Shopping by Yahoo, and MSN Shopping by Microsoft, etc.

In addition to online retailing, comparison-shopping was already established in online travel due to the travel industry's well-developed technology infrastructure, which dated back to the 1950s. In this category, we observed not only well-established services like Expedia.com, Orbitz.com, and Travelocity.com but also the agents of agents like Kayak.com, which aggregated and re-packaged information collected from existing comparison-shopping agents.

Comparison-shopping service was also a natural adaptation for finance and insurance businesses that are essentially broker-coordinated. In this category, most comparison-shopping agents served as an additional channel parallel to human brokers interacting with consumers, thus increasing customer experience, e.g. lendingtree.com.

Except in some unique cases (like Pricescan.com), almost all comparison-shopping agents that emerged in this period adopted a cost-per-click (CPC) business model, the model that evolved from Pricewatch.com. The CPC model allows startup agents like shopping.com and pricegrabber.com became profitable without an initial capital infusion by large venture capitals.

Consolidated Comparison-Shopping Services

Starting in 2003, major comparison-shopping services began to acquire more service features in order to compete with each other (Wan, Menon, & Ramaprasad, 2007).

The most notable case was Dealtime's acquisition of resellerratings.com and epinion.com in February and March 2003 respectively. Dealtime.com was mainly focused on price comparison. Resellerratings.com was one of the earliest agent services that focused on collecting ratings about online vendors. Epinion.com specialized in collecting product review information. When these three services merged, online shoppers could obtain in one search almost all they wanted regarding a product and making a shopping decision.

The popularity of comparison-shopping also has spread across national boundaries. In Europe, Kelkoo, which launched in 2000, the same year as Dealtime, experienced multiple mergers with other small Shopbots like Zoomit, Dondecomprar and Shopgenie. Within a few years, it became Europe's largest e-commerce website after Amazon and eBay and the largest e-commerce advertising platform both in the UK and Europe. It was acquired by Yahoo in 2004. Microsoft acquired another leading European comparison shopping service, Ciao, in 2008.

In online traveling, Expedia.com, Travelocity.com, and Orbitz.com became the top 3 consolidators. They integrated the airline, hotel and car rental information into their offerings. As a result of these consolidations, a more mature market structure was formed.

THE DESIGN OF THE SHOPBOTS

Comparison-shopping services are powered by shopbots. The core function of a shopbot is to retrieve data from multiple data sources, aggregate them, and then present them to online shoppers in certain ways so that shoppers can make shopping decisions efficiently.

Existing research on the design of shopbots mainly has two directions: data retrieval and data presentation.

When BargainFinder first emerged on the Web in 1995, price data retrieval and presentation were all integrated. The shopbot was activated by a query from users for a specific music title. The shopbot then searched a few pre-selected online music stores for this title with a pre-coded wrapper. Once it retrieved prices from these sites via the wrapper, it aggregated them. The results were then processed and presented in html format as a response to the user.

This straightforward method was sufficient for a light version service that only crawled a few online vendors, but it was inadequate for aggregating price information from a large number of vendors and complex site and web page structures.

Compared with the simple design of BargainFinder, Killerapp used a database to temporarily store the price data and then update it from time to time. Pricewatch asked its vendors to update its database directly. The latter two represented two distinctive methods of data retrieval: data wrapping and data feeding.

Data Extraction and Wrappers

Even before the emergence of shopbots on the Web, people were already exploring how to retrieve data from the Web. It turns out the biggest challenge was *how to automatically retrieve and integrate information from multiple and heterogeneous information sources in HTML format*. There is a historical limitation in HTML design: the tags used in the programming language are semi-structured, and they only describe how to *display* the data but not what the data is about. For example, the price of a product on an HTML page may have a tag to describe what font style and size should be used to display it in a browser, but there is no way to indicate whether this data is a price and whether it is a price for iPod or something else.

This design limitation posed a considerable challenge for intelligent software to identify a specific piece of information from different websites. Manual configuration of an agent was only applicable to a limited number of websites; thus, there was no scalability. An ideal agent has to automatically search the Web, identify the data organizing patterns, and then retrieve and transform them into a fully structured format. Hence, considerable research efforts were directed on the design of a perfect "wrapper" that could perform these tasks.

Based on the degree of automation, we have three types of wrappers: manual, semi-automatic, and fully automatic (Firat, 2003). The manual wrapper was designed and customized for a specific data source structure; thus, it cannot be used in other places. It also needs to be revised once the data source structure is changed. The semi-automatic wrapper needs manual indication of the structure of the information on Web page, and then the program generates corresponding rules to automatically retrieve the data for similar pages. The fully automatic wrapper uses inductive learning and other artificial intelligence methods to learn and retrieve information from the web page directly. The learning stage usually involves training cases.

Though data wrapping is an independent way for shopbots to retrieve and present information for shoppers, the scalability of this method was limited because of the inconsistency of HTML page design as well as the demand for more complex data that could not be easily analyzed via full automation. Thus, few established comparison-shopping services could expect to expand based on this method only. Most services were using a mixture of both data wrapping and data feeding, as we explain in the next section.

Data Feeding

The data feeding method is essentially allowing or encouraging online vendors to provide their product price data to Shopbots in a specific data format defined by the comparison-shopping service provider. Data feeding technology is simpler than data wrapping, but there is a social challenge in it: online vendors may hesitate to list their goods on a comparison-shopping site to compete with their peers merely on price. This used to be a major concern and also led to some legal issues (Plitch, 2002).

The data feeding method can also be regarded as an online version of the catalog business model. Pricewatch.com was probably the first comparison-shopping services using this method. Back in 1995, instead of crawling the Web, it invited computer vendors to feed the data into its database using its proprietary DataLink system, which was essentially a data feeding system aggregating vendor data input.

The data feeding method is advantageous to comparison-shopping service providers. By using a pre-defined data input format, many errors in data retrieval can be avoided. Also, shopbots can receive more comprehensive information from vendors regarding the product, not only price but also shipping cost, inventory level, discount, as well as other information.

There are also advantages to vendors. They had more control over their presence in comparison-shopping. They could update their price whenever they wanted. Actually with the increasing number of comparison-shopping sites to participate and products to upload, vendors soon found the need to use a specialized data feed management service. Such needs fostered a niche business in managing data feeding to multiple comparison-shopping sites. And it was led by companies like *SingleFeed* and *FeedPerfect*. These companies allowed a vendor to upload the product data to their site, and then they would publish the data in all those leading comparison-shopping sites. Vendors then could manage their data from a single point instead of logging into each shopbot. More sophisticated services like ChannelAdvisor provided solutions for a vendor to monitor the ROI of its listings so the whole selling process could be more efficient.

The limitation of the data feeding solution is mainly the impact on online shoppers. By asking the participation of online vendors or even charging a fee from online vendors to participate, the comparison-shopping site essentially transforms itself from a buyer's agent into a seller's agent. So the welfare of consumers may be compromised.

Though data extraction and data feeding are two different technology tracks, most established comparison-shopping services use both technologies to optimize their offering. Data feeding is generally the major data retrieval method while data wrapping is complementary. This mixed solution trend is dominant currently.

Data Presentation

Regarding how to present the comparison data in a most effective way, there are several important findings since 2000.

First, the current data presentation style may overload online shoppers by too many choices. The popularity of comparison shopping among online shoppers has attracted many online vendors to participate. As a result, we consumers experienced an increasing number of offerings for the same product from the popular comparison-shopping sites. It is not uncommon for a shopper to get more than one hundred selections for one popular electronic product when searching a comparison-shopping site.

Screening and making a decision become more and more stressful in such situations, and consumers may be overloaded by so many choices. Indeed, in one research by Iyengar and Lepper (2000), they found that when exotic jam was offered to customers in a local grocery store, the probability that a customer would buy one was negatively related to the number of different choices presented to them. In other words, the more choices available, the less likely they were to make the purchase. Wan (2005) designed an experiment to test similar symptoms in a Web-based comparison-shopping environment. It was found that when the number of choices and/or number of attributes for each choice exceeded certain limits, the decision quality decreased dramatically.

Though choice overload could be a big hurdle for current techno-business models of comparison-shopping services, the solution is restricted by service providers' incentives to list more products and generate more revenues. This leads to the second question: Are more listings always good for service providers?

Depending on your own judgement, the answer is probably "no" because it may reduce the purchase rate and eventually decrease their competitiveness compared with other online channels.

In a related study by Montgomery, Hosanagar, Krishnan, and Clay (2004), they assume a scenario in which a shopbot searches all available vendors and retrieves all results to the shopper. However, because there is a waiting time cost to the shopper as well as redundant or dominant choices being unnecessarily presented, the utility of the shopper was compromised. Thus, they proposed that shopbot designs can be improved by developing a utility model of consumer purchasing behavior. The shopbot could utilize this model to decide which stores to search, how long to wait, and which offers to present to the user. Because this utility model considers the intrinsic value of the product and its attributes, the disutility associated with waiting, and the cognitive costs associated with evaluating the offers retrieved, it could increase the utility of the user. They use six months of data collected from an online book comparison shopping site to demonstrate the effectiveness of their model.

Empirically, by intelligently filtering the choices and removing those obviously dominated choices, comparison-shopping service providers could save response time, reduce overhead traffic, and mitigate the choice overload impact on shoppers. Eventually, such design may improve the purchase probability and thus increase the revenue as well.

HOW SHOPPERS USING THE COMPARISON-SHOPPING SERVICES

Though shopbots are being implemented in different technologies, sometimes as far from each other as complete data feeding is from data extraction -- from consumer perspective, such differences are transparent. For most online shoppers, comparison-shopping services decreased their search cost and thus potentially increased the welfare of the consumer.

However, certain shopper behaviors prevent consumers from fully utilizing the characters and features of comparison-shopping services. Thus, more research is needed in this area to help us better understand the interaction pattern between shoppers and shopbots.

We review this topic by first explaining how online retailing is different from its brick and mortar counterpart. Then we review existing research on user behavior when interacting with shopbot-like agents. After that, we review major theories that can be used to further explore this issue.

The Significance of Online Retailing

The emergence and commercialization of Internet provides a completely new channel for consumer shopping – online shopping. Compared with traditional channels, this online channel has two distinctive features: a low entry barrier and almost unlimited shelf space.

As described in the seminal book "*Information Rules*" (Shapiro & Varian, 1998), the online channel has an unprecedented low entry cost for potential retailers. Nowadays, any individual can launch an ecommerce site by uploading the product data to a template provided by ISPs with only slight customization of the interface. As a result, there are an increasing number of small online retailers that are operated by only one or two individuals.

Online retailers also have the unique privilege of almost unlimited shelf space. For example, Wal-Mart, the world's biggest brick-and-mortar chain store, at any one time has 100,000 items available on the shelf in a typical Supercenter. However, Amazon.com, the biggest online store can already offer as many as 18 million unique items even without the consideration of third-party vendors who utilize the platform provided by Amazon to sell their own customer base.

These two features have led to an exponential increase in product offerings online in the past 10 years, which have enriched our shopping experience. However, with so many vendors available online, finding them and the products they offer is not as easy as expected unless one is very savvy in searching the Web. In most cases, online shoppers eventually make their purchase from a few established online portals like Amazon.com. Thus, comparison-shopping services have become a necessity for helping consumers locate the best price from the inside of the Web.

Theories on User Shopping Behavior

To design an interface of shopbots that could accommodate the decision-making behavior of shoppers, the following theories have been used in research on shopping behavior by many existing studies and maybe useful.

Multi-Attribute Utility Theory

Generally speaking, any individual decision task that involves choosing from several alternatives can be considered as a preferential choice problem. The normative theory to explain such a process is multi-attribute utility theory, or MAUT (Raiffa & Keeney, 1976). Early applications of MAUT focus on public sector decisions and public policy issues. These decisions not only have multiple objectives but also involve multiple constituencies that will be affected in different ways by the decision. Under the guidance of Ralph Keeney and Howard Raiffa, many power plant decisions were made using MAUT. The military also used this technique because the design of major new weapons systems always involves tradeoffs among cost, weight, durability, lethality, and survivability.

MAUT assumes the decision-maker can subjectively assign a weight to each attribute and calculate the utility of each choice by multiplying the weight and value of each attribute then adding them together. As a result, each alternative has a corresponding utility. Comparison can be performed and a decision can be made by choosing the alternative that has the highest utility. MAUT is a normative decision-making theory in the sense that it tells us what we "ought" to act based upon measurements of our utility for different criteria and combinations of them.

It turns out the default design for many comparison-shopping services is based upon MAUT. For example, most shopbots list their offerings in a tabular format and allow customers to compare choices by their aggregated utilities. Some experiments indicated that using a shopbot designed on this principle could increase the efficiency and effectiveness of decision-making in general circumstances (Haubl & Murray, 2003; Haubl & Trifts, 2000).

However, empirical research also found that consumers do not always make decisions based on MAUT because of its relative high demand for cognitive efforts. This is especially true when online shoppers are making trivial shopping decisions, e.g. buying a $10 paperback bestseller. In such cases, when consumers have to choose from many alternatives, instead of making thoughtful comparisons as described in MAUT, they may use heuristics.

Heuristic and Heuristic Strategies

Heuristics are frequently observed in humans' decision-making process due to a lack of complete information as well as limited cognition (Simon, 1955, 1956). While Simon's model was widely accepted by decision-making researchers, it was too general to answer specific questions about why a decision-maker opts for one particular choice over others. Research on cognitive heuristics and adaptive algorithms provides a better explanation.

Payne, Bettman, and Johnson (1993) proposed a contingency model of decision-making and conducted a series of experiments to examine how decision-makers use heuristics when being presented a decision task with many similar choices. Based on Herbert Simon's "bounded rationality" theory, Payne and his colleagues regard the human mind as a "limited-capacity information processor" with "multiple goals" for a specific decision-making problem. Because of the limitations of the human mind, decision-makers tend to use various heuristic strategies to make decisions. These heuristic strategies can be roughly divided into two categories: compensatory and non-compensatory. Compensatory strategies are normative strategies that emphasize the consideration of all relevant attributes for each choice, while non-compensatory strategies are heuristics that emphasize saving efforts and only focus on relevant attributes. Among these, elimination-by-aspects (EBA) or "row-based" elimination strategy (Tversky, 1972) is probably the best match to shoppers' behavior when using comparison-shopping services.

When decision-makers or shoppers face many choices, they usually switch from compensatory strategies to non-compensatory strategies (Einhorn, 1970; Tversky, 1972). But most non-compensatory heuristics could eliminate potentially high-quality choices. Thus, when online shoppers are provided with an increasing number of choices by shopbots, the quality of their decision may decrease. As mentioned in the previous section, a better design of the shopbot could mitigate this problem. But fundamentally, the data feeding business model motivated the service provider to cram as many options as possible into the response page for consumers. A better solution might lie in the revision of both the technology and the business model.

The Least Effort Principle

If consumers are provided with better designed shopbots and comparison tools, will they be able to use them to make a better choice?

As discussed in previous sections, in the rational view, decision-makers should always use strategies that optimize the decision outcome. In reality, heuristics are frequently used when people make choices. These heuristic behaviors are usually not the strategies that lead to optimal outcome, but they are quicker and easier to perform. This phenomenon was probably first systematically observed by Zipf (1949), who used the term *principle of least effort* to describe it.

According to Zipf's least-effort principle, the decision-maker adopts a decision strategy not solely based on the decision quality the strategy produces but also intuitively considers the effort a strategy demands. As long as the minimum decision quality is met, the strategy that requires the least cognitive effort will be adopted–usually those very familiar and fully routinized heuristic strategies. The least-effort principle tells us that human beings always try to minimize their effort in decision-making as long as the decision quality meets the minimum criteria.

The least-effort principle was observed in experiments conducted by Todd (1988) and Todd and Benbasat (1992, 1999). In their experiments, when provided with both compensatory and non-compensatory tools in a shopbot-like interface with decision tasks, consumers chose to use non-compensatory tools, though the compensatory tools would have generated higher quality results. Subjects merely chose a satisfying result and reserved effort for harder decisions.

The Cognitive Process of Decision-Making

Online shoppers' behavior with comparison-shopping services may also relate to their own shopping experience and their familiarity with the product or services.

From this perspective, it is generally believed that there are three types of consumer decision-making modes. They are routinized response behavior (RRB), limited problem solving (LPS), and extensive problem solving (EPS) (Howard, 1977). From RRB to EPS, consumers become less familiar with the products so they need more effort and routines to conduct the decision-making task. In the RRB mode, decision-makers are very familiar with the product they are looking at; they are more concerned with impersonal information (price, after-sale service quality, etc.). In EPS mode, decision-makers are very unfamiliar with the product, so a lot of additional cognitive effort is invested in forming the concept of the product, in addition to processing impersonal information.

So far there is little research that addresses the familiarity and experience issue in comparison-shopping.

COMPARISON-SHOPPING AS A NEW SALES CHANNEL

With the popularity of comparison-shopping, more and more small vendors found it an effective channel to reach more price sensitive customers. Thus, they have the incentive to use the shopbots proactively as new sales channels. Because of this, those established comparison-shopping services could command a premium participation fee as well as a referral fee from small online vendors.

Because of the competition pressure from peers, many vendors found it important to list their product on not only one comparison service but all those used by their competitors. On the other side, there is a fixed cost for each participation and a variable cost for each referral that may or may not lead into a sale. Thus, if we consider each comparison-shopping site as a channel to reach consumers, it is important for an online vendor to formulate a viable channel selection strategy. It could be identifying one most profitable channel or a combination of channels.

From a sales and marketing channel perspective, there are two types of comparison-shopping services, those general ones that provide comparison-shopping for multiple categories of commodities or even services (e.g. shopping.com or pricegrabber.com); and those specialized ones that provide comparison service for a single or a few closely related commodity categories (e.g. book price comparison site addall.com or computer and accessories comparison site pricewatch.com).

Depending on the business, choosing a general or a specialized comparison-shopping service or a combination of sites may have different effects on the business's sales performance.

THE IMPACT OF COMPARISON-SHOPPING SERVICES

How will comparison-shopping influence and shape the landscape of electronic commerce or the economic status quo in general?

Empirically, comparison-shopping has established its position among the top 3 online shopping options, together with online retailing and online auction. Since 2003, the traffic rank for the leading comparison-shopping service provider, shopping.com, has been right after Amazon and eBay among major B2C ecommerce portals, as measured by comScore and other Internet Information Providers.

Comparison-shopping also significantly changed the pricing structure of certain service sectors. For example, in an empirical study by Brown and Goolsbee (2002) on comparison-shopping sites for life insurance policies, they found that with micro data on individual insurance policies and with individual and policy characteristics controlled for, increases in Internet use significantly reduced the price of term life insurance. Such increase did not happen before the comparison sites began, nor for insurance types that were not covered by these sites. They also found that such usage reduced the term life price by 8 to 15 percent.

However, the impact of comparison-shopping is also limited by other product and service factors. For example, Brynjolfsson and Smith (2000) found that when consumers use price shopbots to search for price information on books and CDs, instead of picking the online book vendor offering the lowest price, they tended to choose the branded vendor who charged the lowest premium price. As a result, even faced with price competition from small online vendors via comparison-shopping services, branded online vendors like Amazon.com could still command a premium price on products.

Thus, we may conclude that though there are impacts of comparison-shopping on the pricing structure of products and services, exactly how such impacts work out on different products and services needs to be explored separately. It depends on many factors like the complexity in evaluating the quality of the product or service.

In a forward look, Kephart and his colleagues simulated a software bot-enabled electronic commerce market where "billions of software agents exchange information goods with humans and other agents," of which, shopbots is one important software agent category (Kephart & Greenwald, 1999, 2000; Kephart, Hanson, & Greenwald, 2000). Through simulation on different pricing behavior of Shopbots, it was found that both beneficial and harmful collective behaviors that could arise in such system, which could lead to undesired phenomena.

COMPARISON-SHOPPING IN ONLINE TRAVELLING AND HEALTH CARE

In addition to the commodity market, comparison-shopping is also widely adopted in many service sectors like online travelling and health care.

Because of the existence of agents in many service sectors, computerized comparison information was already available before the emergence of the Web. For example, the SABRE system of American Airlines began to provide airfare comparison service for its agents back in the 1960s. So for those already computerized service sectors, migration to the Web is largely a shift for consumers to get information from comparison-shopping agents instead of the traditional human agents.

Travelling

Unlike online retailing, which has been a relatively new innovation since 1994, the travel industry was "wired" much earlier and has more sophisticated information aggregation and comparison technology except that it is the agent, not consumers, who can access the information. This was especially the case for the airline industry.

Back in the late 1950s and early 1960s, due to the tremendous growth of the number of air travelers and increasing size of airplanes, the traditional manual reservation and ticket inventory checking solution could no longer keep up with the demand. As a result, major airline companies began to develop fully automated airline reservation systems like SABRE with the technical assistance of IBM and other IT companies. The main purpose of these systems was to connect the reservation with the seat inventory information so people could check the availability of seats in real time and make reservations on the spot. Once these systems became stable, major airlines realized that they could outsource the ticket booking function to travel agents. Thus a new competition emerged between major airlines to compete for travel agents to use their systems. Small airlines also decided to join such systems so their flight and ticket information could also be accessed by agents. SABRE and Apollo became two major systems, and they were called consolidators. Gradually, agent-oriented comparison-shopping infrastructures were established within such systems.

With the introduction of the Web, many travelling companies found they could sell directly to customers. Thus, the agent-mediated market structure was transformed, and traditional agents were dis-intermediated. The debut of Expedia.com by Microsoft in 1996 ushered the travel industry into this new competition age. SABRE also launched Travelocity.com in the same year in order to compete. With the integration of car rental and hotel information systems, the so-called Global Distrubtion Systems were formed. Currenlty, the three major competitors are Expedia.com, Travelocity.com and Orbitz.com.

Meanwhile, shopbots was also characterized by continuous innovations. The most notable one included the derivative comparison-shopping agents, like Kayak.com, that could retrieve information from existing comparison-shopping services (Wan et al., 2007); and the ITA software, which focuses on calculating optimal travel routes.

Health Services

The scenario of health services is different from online travel.

On one side, services like health insurance were transformed on the Web very early. Comparison-shopping on the best insurance rates was available in the mid 90s, if not earlier. This is because insurance industry is coordinated by brokers and it is a natural extension for brokers to set up a Web presence, basically another channel for attracting consumers.

On the other side, comparison services on in-patient/operation cost, hospital/clinic/doctor evaluation information, and pharmacy cost, etc. are lagging behind and only became available recently.

Pharmeutical cost was the second comparable information category available on the Web. Major players include destinationrx.com and pricerx.com. The in-patient/operation cost information as well as evaluation information for hospital and doctors are probably the most important health information a consumer needs to know.

One reason for pharmeutical cost lagging behind is that information is only available via non-profit organizations or government agencies like the US Department of Health and Human Services (www.hospitalcompare.hhs.gov), which provides comparison information on hospitals, and the Joint Commission (www.jcaho.org), which provides information on hospitals as well as other health care service providers. The latter is responsible for accreditation and certification of hospitals, which allows it to get such information on quality of services during evaluation.

Recently, some state governments began to provide evaluation information for hospitals and doctors. Massachusetts Health Quality Partners (MHQP), for example, is an independent state agency that monitors the quality of health services in Massachusetts. It provides side-by-side comparisons to its residents on the quality of service of clinics in the state.

Recently, a few commercial sites began to integrate this information and provide their users a comprehensive comparison-shopping environment. Vimo was probably the first one. According to the site launched in 2006:

"Vimo is the nation's first integrated comparison-shopping portal for healthcare products and services. On January 24, 2006 we launched a website that allows businesses and consumers to research, rate and purchase health insurance plans and Health Savings Accounts (HSAs), and choose doctors from across the country. Vimo brings together a variety of private and public data sources so that shoppers can find a physician and compare hospital prices for medical procedures. Vimo users can read and post reviews about any of the services or products available." Source URL: http://www.vimo.com/html/about.php

It turns out that collecting feedback from patients about hospitals, doctors and dentists is not a technical challenge for most heath-related sites. There are many Websites that help people find doctors, hospitals, dentists, etc. But few of them ask the patient to provide feedback. It is understandable that such sites survive on referral fees paid by doctors, but they may not realize that by accumulating feedback information from consumers, they become the Amazon of health care. In contrast, established online portals do not have such conflict-of-interests concerns so the feedback features are added naturally on their health-related site, like the recently launched local dentist evaluation in Live Search by Microsoft.

With the information revolution in health services, comparison-shopping would become easier and more efficient in this sector. We expect more research in the future on this topic.

FUTURE RESEARCH

There are many interesting directions for the future research of comparison-shopping services and the design of shopbots.

Mobile Comparison

With the ubiquitous of Web-enabled mobile devices like iPhone, comparison-shopping services could be extended into the brick-and-mortar store. Services like Frucall already allow consumers to comparison-shop a product in a store with the same product offered by online stores. All customers need to do is provide the bar code or ISBN of the product via their mobile device.

There is another innovation to provide a comparison for a product between online and local offerings. For example, ShopLocal.com provides product price comparisons from popular online stores as well as local stores based on a zip code provided by the user.

It is probably a natural move for future services to combine both mobile comparison and local comparison so consumers can get price quotes on the spot from both online and nearby brick and mortar stores.

We expect such services may not only change the price structure but also the product portfolio for both online and local stores.

Bundled Comparison

Though comparison-shopping has been around for 13 years, there is still relatively little progress in bundled comparison. That is if a consumer wants to buy several products, he may wish to compare bundled offers instead of comparing each individual piece. A simple example is buying textbooks at the beginning of the semester: students may want to buy all textbooks from one book store that offers the best price instead of comparison-shopping each one separately.

Currently, a UK-based comparison-shopping service, mySupermarke.co.uk, does provide bundled comparison for groceries. Shoppers could select multiple groceries and put them into their online shopping cart. The service could calculate which local grocery store could offer the best price for them, and the shopper could be redirected to the grocery website to complete the transaction. Around 2006, the company claims an average online grocery cart includes approximately 50 items, with a total cost of between $160 to $220. Consumers could save an average 20 percent per cart.

How to design such agents to provide bundled comparisons for other commodities and services could be an interesting challenge.

Feature and Function Comparison

Most comparison-shopping services focus on price comparison on the same product offered by different online vendors. A few provide limited feature and function comparison across similar products. There is no comparison across product categories. On the other side, new products are being invented every day. Many of them serve the same function needs but belong to different product categories. Thus, it will be helpful if a comparison-shopping service could allow consumers to select products based on a specific feature or function.

CONCLUSION

In this overview, we covered several major topics of comparison-shopping service and agent design. We demonstrated that though comparison-shopping services have developed into a popular online shopping channel, there are many issues that need to be investigated about this new phenomenon. In addition, the innovation on comparison-shopping service and shopbots design is still far from satisfactory. We expect this book could provide some aspirations for new research and innovation in this area.

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KEY TERMS

BargainFinder Experiment: In 1995, a shopbot named BargainFinder was launched by a group of researchers in then Andersen Consulting to test the reaction of consumers and online vendors. It received major media coverage and became one of the first shopbots that came into public attention.

Bundled Comparison: A feature of comparison-shopping service that allows shoppers to compare price for multiple products as a whole offered by different online vendors.

Choice Overload: A scenario when a consumer is being overwhelmed and hesitating to make decisions when facing with too many choices.

Comparison-Shopping Services: The Web-based services that online shoppers use when they try to find product prices and other related information aggregated from multiple vendor sites.

Data Feeding: A data retrieval technique that allow users to feed information into a shopbot database in a pre-defined format. Data feeding was widely used in popular shopbots.

Data Wrapping: A data retrieval technique that can be either automatically or manually created to identify information contained in a HTML web page and then transform them into a consistent format for further processing. Data wrapping technology was widely used in early shopbots.

The Least Effort Principle: A decision-making theory that human beings always try to minimize their effort in decision-making as long as the decision quality meets the minimum criteria.

Mobile Comparison: A feature of comparison-shopping service that allows a shopper to interact with shopbot via mobile devices.

Multi Attribute Utility Theory: A decision-making theory that assume human beings can subjectively assign a weight to each attribute and calculate the utility of each choice by multiplying the weight and value of each attribute then adding them together. As a result, each alternative has a corresponding utility. Comparison and a decision can be made by choosing the alternative that has the highest utility.

Shopbot: The software agent powered the comparison-shopping service. Though there are variations in design and implementation for different services, the basic functions include data gathering, storage, and presentation. There are two main data retrieval methods: data wrapping and data feeding.