A SURVEY OF THE COMPARISON SHOPPING AGENT-BASED DECISION SUPPORT SYSTEMS

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ABSTRACT

The web-based comparison shopping agents (CSAs) or shopbots have emerged as important business intermediaries that provide decision support to both the shoppers and the merchants. The basic idea is to provide an easy access to both the price and non-price based competitive features to shoppers. The CSAs do not have an equivalent counterpart in the offline world and they have generated a significant amount of interest among researchers in economics, marketing, and information systems fields. There have been numerous studies on the CSAs in the contexts of price dispersion, consumer behavior, search costs, and recommender systems. The focus of this paper is to study the contemporary literature about the CSAs to analyze them in the context of decision support systems (DSS). In order to provide comprehensive decision support, a typical DSS should have four components: data, models, interfaces, and user specific customization. In this paper, this four component framework is used to synthesize the current research work in the context of DSS and to explore contemporary CSAs. The paper provides suggestions for improving the decision support aspect of the CSAs and proposes a research agenda for the CSA-based decision support systems.

Keywords: comparison shopping agents, CSA, shopbots, comparison shopping, decision support systems

1. Introduction

The advent of the Internet has created new avenues for the merchants to sell their products and has also reduced the barriers for entering into retail business. This, along with the expanded reach of the Internet retailing and widely discussed 'long-tail' phenomenon, has generated intense competition in the online retail sector. In the online domain, the oligopolistic nature of the brick and mortar (B&M) retailing has virtually become open-for-all type of retailing. This has increased the number of available options for the shopper's purchasing decisions and merchant's marketing decisions. As the optimal decision-making involves thorough comparison and analysis of all alternatives on hand, the increase in number of available options has made users' decision problems more complex. Moreover, such complexity is compounded by the fact that as compared to their B&M counterparts, online merchants are more diverse. They are not only heterogeneous in terms of the services that they provide, but also differ in other areas such as the type of products that they stock (e.g. regular, refurbished, used, outdated, or long-tail) and the channel-mix of their operations (e.g. pure-play, click and mortar (C&M), and manufacturer-owned). It is no wonder that in the days of the Internet, intermediaries have occupied a prominent space in facilitating the decision making process of both the merchants and the shoppers. Majority of these Web-based intermediaries bring merchants and shoppers together and facilitate a successful sales transaction.

One of the most popular forms of the Web-based intermediaries is the comparison shopping agents (CSA) or shopbots. CSAs provide decision support tools to shoppers for comparing their purchase alternatives based on both the price and non-price (e.g. product, merchant reputation) based factors. They are increasingly becoming popular among shoppers. The report from a leading Web-analytics firm, *Compete,* shows that each of the top two major CSAs, Nextag.com and Bizrate.com, has attracted more than two million unique visitors during January 2009. It is not surprising to see that major Internet companies like *Microsoft*, *Yahoo*, and *Google* have integrated comparison shopping in their search-based solutions. The CSA-based decision support systems are also proactively integrated by some merchants like *Buy.com*.

CSAs do not have an equivalent counterpart in the offline world and they have generated a significant amount of interest among researchers in economics, marketing, and information systems fields. There have been numerous studies about the CSAs in the contexts of the price dispersion [Brynjolfsson et al. 2000; Clay et al. 2001; Baylis and Perloff 2002; Clemons et al. 2002; Baye and Morgan 2004; Baye et al. 2004], consumer behavior [Pendersen 2000;

Sproule and Archer 2000; Yuan 2002; Haubl et al. 2004; Brynjolfsson et al. 2007], information search costs [Bakos 1997; Trifts and Haubl 2003; Janssen and Moraga-Gonzalez 2004; Venkatesan et al. 2006; Waldeck 2006], and recommender or reputation systems [Haubl and Murray 2003; Garfinkel et al. 2006; Xiao and Benbasat 2007; Garfinkel et al. 2008; Saastamoinen 2009]. These studies have highlighted the influential role of the CSAs for assisting merchants in their competitive price-setting and differentiation-based decisions and helping shoppers in making optimal purchase decisions.

The focus of this paper is to study the contemporary literature about CSAs to analyze them in the context of decision support systems (DSS). In order to provide comprehensive decision support, a typical DSS should have four components: data, models, interfaces, and user specific customization. In this paper, the four component DSS framework is used to survey the current CSA-based research and study the decision support role of the contemporary CSAs. The paper provides suggestions for improving the decision support aspect of the CSAs and proposes a research agenda for the CSA-based decision support systems. Our survey of the literature synthesizes the current CSA-based academic research based on the four major components of the DSS: data, model, user interfaces, and users [Sprague 1980; Bhargava and Downs 1996; Bhargava and Downs 1996; Marakas 2003]. An earlier brief survey about CSAs has been published by Pan *et al.* [Pan et al. 2004]. However, the focus of that survey has been on the price dispersion. Likewise, Xiao *et al.* have briefly discussed CSAs in the context of their survey on recommender agents [Xiao and Benbasat 2007] and Josang *et al.* have analyzed CSAs like Bizrate.com in the context of the trust and reputation systems [Josang et al. 2007]. Our study contributes to the academic literature in this field by adding a DSS dimension to our CSA-based knowledgebase.

The remainder of the paper proceeds as follows. Section 2 provides basic background information about CSAs. Section 3 describes our approach for analyzing CSAs in the context of the DSS. In particular, it summarizes the major components of the DSS against which CSAs are evaluated. In section 4, a DSS-based survey of the CSAs is provided along with the exploratory study to analyze the contemporary CSAs. Finally, section 5 concludes this paper and provides guidelines for the future research agenda and directions towards the future development of CSAs in order to provide comprehensive decision support to the users.

2. Background for CSAs

The CSAs are Web-based agents that receive requests from users for the product-merchant information and then provide a ranked list of the relevant information such as price, delivery options, availability, and warranty [Todd and Benbasat 1992; Yuan 2002]. They facilitate access to a wide range of products across many merchants, and assist customers in obtaining the best value [Xiao and Benbasat 2007]. The earliest CSA was Anderson Consulting's BargainFinder. It allowed a user to enter the name of a music album or a band and then it would search for the user's selection at nine merchants to return the ranked price list to the user [Smith 2002; Wan et al. 2007]. Subsequently, many other CSA-based business models have emerged. Michael Smith classifies CSAs into three broad categories: stand-alone, contextual, and personalized [Smith 2002]. Stand-alone CSAs provide only price information (e.g. pricescan.com), contextual CSAs present both price and detailed product information (e.g. CNet.com), and personalized CSAs offer customized prices, information, and interfaces (e.g. Frictionless.com and Value Shopper) [Smith 2002]. Another way of classifying CSAs is based on their relationship with the merchants. CSAs like Google shopping which directly gets price quotes for products from sellers' websites are merchant independent, while CSAs such as Pricegrabber.com which receives price quotes for products directly from sellers are merchant dependent [Wan, Menon et al. 2007]. Currently majority of the popular CSAs (e.g. Bizrate.com, Nextag.com, Shopzilla.com, and Pricegrabber.com) are merchant-dependent and contextual and provide product, price and merchant related information to the shoppers.

In their initial versions, CSAs were widely used as search engines and mainly focused on giving price comparison results [Haynes and Thompson 2008]. During this time, CSAs had no formal relationship with the merchants and they used to obtain price quotes from the merchants by downloading and parsing HTML pages in real time. Many merchants , fearful of downward pressure on prices, remained hostile to CSAs and sometimes adopted obstructive tactics and even blocked their access to merchant information [Crowston and MacInnes 2001]. Realizing the importance and popularity of CSAs, now merchants have proactively started participating and collaborating with CSAs. Hence, CSAs are truly acting as an infomediary, or a Web-based intermediary, facilitating sales transactions between merchants and shoppers.

The CSAs have become very popular among shoppers and comparison shopping is considered to be one of the most significant advantages of the electronic commerce [Alba et al. 1997]. Burke shows that more than 80 percent of the survey respondents were enthusiastic about using Internet for comparison shopping [Burke 2002]. During the 2003 holiday season, 22 percent of the shoppers used CSAs to begin their shopping [Xiao and Benbasat 2007]. Contemporary literature in information sciences and economics explains this popularity in terms of the CSA's role in minimizing the search costs. The CSAs reduce search costs for the product and price information by at least 30-fold compared to teleshopping and even more compared to physically visiting B&M stores [Smith et al. 2000].

A typical online shopping process for a shopper starts with a shopper determining a product to purchase [Montgomery et al. 2004]. Then onwards, the shopper can follow various strategies for searching information related to the product, price, or merchants. One possible alternative is to manually visit merchant websites. This has several drawbacks. First, no single merchant may be fulfilling the comprehensive purchase needs of the shopper and hence the shopper may have to visit multiple merchant websites. Second, there are significant learning costs associated with the navigation, search, and shopping process on each individual merchant website. Third, this approach may result in a suboptimal solution because shoppers may be biased towards name-brand merchants [Todd and Benbasat 1992; Menczer et al. 2002] and hence may only visit limited number of options. In such a scenario, the alternative of comparing different options by using the CSA-based decision support tools become more attractive as it reduces search and transaction costs associated with the comparison shopping [Bakos 1997; Smith 2002; Kocas 2003].

As an infomediary, CSAs offer significant benefits to both shoppers and merchants. For the shoppers, they minimize search costs associated with the purchasing of products and also reduce the information asymmetry that exists between sellers and buyers [Trifts and Haubl 2003]. For the merchants, they provide a one click solution for obtaining competitive intelligence. Merchants can use CSAs to observe, record, and process their competitors' product, price, or service offerings. Some merchants like Progressive Insurance and Buy.com have even started providing information about competitor prices directly to their shoppers. These type of CSAs are also known as embedded CSAs [Wan, Menon et al. 2007]. Trifts and Haubl [Trifts and Haubl 2003] show that such actions positively affect the trustworthiness and eventually influence consumers' purchase preferences.

There have been numerous studies about CSAs in the contexts of the price dispersion [Brynjolfsson, Smith et al. 2000; Clay, Krishnan et al. 2001; Baylis and Perloff 2002; Clemons, Hann et al. 2002; Baye and Morgan 2004; Baye, Morgan et al. 2004], consumer behavior [Pendersen 2000; Sproule and Archer 2000; Yuan 2002; Haubl, Dellaert et al. 2004; Brynjolfsson, Smith et al. 2007], information search costs [Bakos 1997; Trifts and Haubl 2003; Janssen and Moraga-Gonzalez 2004; Venkatesan, Mehta et al. 2006; Waldeck 2006], and recommender systems [Haubl and Murray 2003; Garfinkel, Gopal et al. 2006; Xiao and Benbasat 2007; Garfinkel, Gopal et al. 2008]. However, the focus of this study is on the DSS aspect of the CSAs. Prior researchers have discussed the decision support based role of the CSAs. The shoppers' problem of choosing a merchant becomes complicated as the number of alternatives grows [Narayana and Markin 1975]. Hoch and Schkade suggest using a DSS to exploit the relative strengths of human decision makers with complementary technology that can overcome their weakness [Hoch and Schkade 1996]. Haubl and Trifts discuss that CSAs should be seen as a decision tool that supports shoppers in the complex purchasing problem of selecting products and merchants [Haubl and Triffs 2000]. Sproule and Archer consider CSAs as a computer-aided DSS and suggest that they help shoppers in reducing cognitive efforts and allow them to make better purchase decisions by ordering and filtering alternatives [Sproule and Archer 2000]. Likewise, Smith and Brynjolfsson discuss that CSAs can assist merchants in their competitive price setting decisions [Smith and Brynjolfsson 2001]. In the next section, a four-component framework of DSS is explained. This framework will be used to synthesize CSA-based research in the context of DSS.

3. DSS Components

Although, CSAs' role in solving decision problems of the shoppers and merchants is widely discussed, they are not analyzed extensively in the context of DSS. The DSS design literature identifies four major functional components necessary for a DSS – data, models, interfaces, and user-specific personalization [Sprague 1980; Ariav and Ginzberg 1985; Bhargava and Downs 1996; Bhargava and Downs 1996; O'Keefe and Mceachern 1998; Marakas 2003]. Prior researchers have widely discussed the importance of acquiring and organizing relevant data, developing and managing quantitative models and rule-based algorithms, easy and efficient interactive user interfaces, and user specific focus and customization [Liang 1985; Ma 1997; Shaw and Subramaniam 2001; Nemati et al. 2002; Shim et al. 2002] in order to provide efficient decision support to users.

The data management component is an essential function of the DSS that assists in storing, retrieving, and manipulating data. It typically consists of a DBMS, data directory, query facility, and middleware to connect the DSS with other systems. A typical DSS typically assists in solving semi-structured problems where analytical models are used for the inferential retrieval of data from the database [Bonczek et al. 1982]. User interfaces handle the dialogue between the user and the system. It not only presents the output of an analytical model to the user but also have a dialogue-control system which manages user inputs and makes the entire mechanism user-driven [Ariav and Ginzberg 1985]. Finally, individual user-based customization is an integral part of the DSS because a typical DSS is aimed towards assisting an individual to optimize her decisions and require integrating user-specific requirements into the system. In order to provide comprehensive analysis of the CSAs in fulfilling their role as DSS, it is important to synthesize the current literature in this field based on these components and analyze them with respect to how effectively they perform in each of these components.

The CSAs exist in various product-based domains including service industry specific (e.g. travelocity.com and expedia.com), product specific (e.g. bestbookbuys.com for books), or general for various products and industries (e.g. pricegrabber.com). In order to link the academic research with the practical deployment of DSS, the features of a sample of CSAs are explored by visiting their websites. In the next section, a detailed synthesis of CSA-based literature is provided in the context of the DSS along with an exploratory study of a sample of CSAs to link the academic research with the practical deployment.

4. DSS-based survey of CSAs

The four-component framework of DSS is used to synthesize the research in this field and to analyze how CSAs assist users in providing solutions to their purchasing decision problems.

4.1. Decision Problem

A typical DSS assists users in solving decision problems. CSAs are considered as decision systems that provide support to shoppers in their purchase decision making process [Haubl and Triffs 2000; Smith and Brynjolfsson 2001] and to merchants in making their pricing and target marketing decisions [Smith and Brynjolfsson 2001; Trifts and Haubl 2003; Chen and Sudhir 2004]. In order to provide decision support to shoppers, a typical DSS should provide basic support during purchase decision making process [Gentry and Calantone 2002]. Moreover, it should also have features to support various contextual scenarios such as bundle purchase or shopping cart comparison [Garfinkel, Gopal et al. 2006; Garfinkel, Gopal et al. 2008].

Purchase process: The shoppers follow a two stage purchase decision making process. In the first stage, they decide what to buy (i.e. shopping) and in the second stage they make a decision regarding from where to buy (i.e. procurement) [Gentry and Calantone 2002]. The shoppers typically use CSAs, once they have already determined what they want to buy, and usually search for the specific item on a CSA or land on its page through a search for the item on a search engine such as *Google.com*. Still, majority of CSAs facilitate shoppers to search for a product category and allow users to compare products to assist them in their 'what to buy' stage of decision making. Moreover, CSAs have sorting and filtering tools for selecting a specific item based on product-specific parameters. For example, the search for 'digital camera' on the major CSAs provides a product summary, price range, and number of sellers information and further allows users to filter these results by optical zoom, price, brand, megapixels, or user ratings. Some CSAs like Bizrate.com provides additional information about what other shoppers are buying, which may assist shoppers further in making their purchase decisions. For the second stage of purchase decision making (i.e. 'from where to buy'), CSAs facilitate purchase decision making by providing both price and non-price related information.

Contextual scenarios: Although, CSAs provide basic decision support for the shoppers' purchasing decisions, they do not consider various important contextual scenarios such as B&M purchase, integration of coupons and rebates, bundle promotions, and shopping cart comparison . Shoppers' decision problems under such contextual scenarios are complex. Prior researchers discuss that the majority of the current generation of CSAs address shoppers' decision problems only during online shopping and ignore the B&M shopping scenarios [Lee and Seo 2006]. *Shoplocal.com* is one of the very few CSAs, that assists shoppers in determining 'what to buy' and 'from where to buy' in both online as well as B&M purchase scenarios [Wan and Peng 2010]. Likewise, current CSAs have adopted one-product-at-a-time search approach [Garfinkel, Gopal et al. 2006]. Majority of mainstream CSAs do not assist shoppers when they want to purchase multiple products. However, some niche CSAs like *dvdpricesearch.com* for movies and *booksprice.com* for books allow shoppers to compare the entire cart of products from multiple merchants. Garfinkel et al. discuss that current CSAs are not effective in providing best value to the shoppers when merchants offer bundle promotions [Garfinkel, Gopal et al. 2006; Wan and Peng 2010]. Garfinkel et al. argue that in order to provide comprehensive decision support to shoppers, CSAs need to reduce the search costs associated with product, price, promotions, and merchants [Garfinkel, Gopal et al. 2008]. They show that the current version of CSAs does not provide effective decision support for finding out products (i.e. product recommendations) and integrating promotions, which may eventually produce suboptimal solutions for the shopper's purchase decision making problem.

Thus, although CSAs provide excellent support for the two-stage purchase decision making process, they do not effectively integrate various contextual scenarios that may provide additional value proposition to the users.

4.2. DSS Components

Data**:** The database management component of the DSS focuses on extracting, storing, and selecting data for providing decision support to the users. In the past, majority of the CSAs deployed screen scraping methods to collect product and price related data from the merchant's website. Once a user submits a query for a product, the CSA initiates a broader search across multiple merchants, downloads their product specific pages, parses them, and presents results to the user [Smith 2002; Montgomery, Hosanagar et al. 2004]. While this method of data collection was popular in the past because of its merchant-independence, it has some severe limitations. First, because merchants were hostile towards CSAs, they used to block CSAs' requests [Todd and Benbasat 1992]. Second, unless a CSA's parsing algorithm is frequently updated, this method is very likely to have data quality issues if the format of the merchant's website is changed [Todd and Benbasat 1992]. Third, merchants may adopt a variety of obfuscation and bait-and-switch strategies in order to reduce the effectiveness of the CSAs [Smith 2002; Ellison and Ellison 2004]. Merchant-independent CSAs have not survived because of these reasons. Today's CSAs collect product catalog data directly from vendors by means of database, web search, Web services, or XML [Fasli 2006]. For example, Google Shopping indexes products from multiple websites in two ways (i) merchants submit product catalogues to Google. (ii) Google identifies web pages that offer products while it searches and indexes the Web [Fasli 2006]. While, merchant-supported model of data collection makes CSAs less vulnerable for data quality issues, it still has some potential issues that may make shoppers' purchase decision making less effective on CSAs. First, merchants pay fees to the CSAs for listing their products as well as any leads that they provide in the form of click-throughs. Because of this, most of the CSAs present a biased marketplace in favor of the merchants. This may provide a sub-optimal solution to the shopper's purchase decision making problem, as the participating merchants may not offer the best prices [Menczer, Monge et al. 2002]. Second, the data are being collected at the discrete intervals rather than on-the-fly. This may create inconsistency between the price on the CSA's website and the actual selling price on the merchant's website. Such a misrepresentation of the price information may lead towards a suboptimal solution for the shopper's purchasing decision problem [Sadeddin et al. 2007].

Majority of the contemporary CSAs needs extensive data that need to be updated frequently and they have started using data warehouses for organizing and storing their data. The success of managerial decisions is critically dependent upon the availability of the high quality integrated data. The data warehouse satisfies this need and hence has become extremely popular. One of the most important properties of the data warehouse is the time-invariant nature of data. Even though, CSAs have started using data warehouse as a primary way of storing data, the usage of time-invariant nature of data for trend analysis and prediction is not evident.

Consumers may seek a variety of information for making their purchase decisions. Current research in the field of information systems, marketing, and economics suggests that price dispersion remains persistent even in the absence of any significant search costs. The major reasons behind this are cost heterogeneity [Thompson 2006; Haynes and Thompson 2008], retailer heterogeneity [Smith and Brynjolfsson 2001; Haynes and Thompson 2008], consumer heterogeneity[Janssen and Moraga-Gonzalez 2004; Waldeck 2006] and obfuscation [Ellison and Ellison 2004]. This shows that both price and non-price factors are still very relevant for making purchase decisions. Prior research suggests that price, online word of mouth, and vendor brand awareness are important data for comparison shopping [Xu and Kim 2008] and suggest that in order to provide comprehensive search costs-based solutions to shoppers, CSAs should provide information about all four 'P's of marketing – products, price, merchants, and promotions [Garfinkel, Gopal et al. 2008] .

Models: The CSAs have been using various types of models to facilitate comparison shopping. These models can be classified into two categories: operational models and analytical models. Operational models are used for core functions such as data extraction, search algorithms, parameter-based filtering, sorting, and merchant-listing. In the past, CSAs used syntax-based data extracting in which they employed heuristics for extracting well-structured data from the HTML pages [Fasli 2006]. Such heuristics are ad-hoc, challenging, merchant-specific, time consuming, and required to be updated as and when merchants make changes in their web pages. As majority of the current CSAs are also provided data by the merchants themselves, this problem does not exist anymore. The usage of models in CSAs is mainly for the operational purpose such as auction models for listing products. Predictive, optimization, or recommendation types of models have not been adopted by mainstream CSAs yet[1].

Prior researchers have suggested various contextual situations where usage of such models may be able to provide significant benefits for the CSA users. Chen and Sudhir show that on the one hand CSAs reduce the search costs for the shoppers and thereby create a downward pressure on merchants' prices [Chen and Sudhir 2004]. However, on the other hand, the merchants can price discriminate between price-sensitive and loyal customers and increase their profitability. The CSAs can use economic models to determine price sensitivity of the shoppers and

[1] Some of the niche CSAs in the online travel industry such as *farecast.com* not only facilitates comparison shopping but also uses data mining to predict the future price trend and suggest whether the shopper should purchase the flight ticket right away or wait Montgomery and Smith (2008). Such information assists shoppers in deciding about purchase timing for the flight ticket.

assist merchants in their target marketing. Likewise, Smith and Brynjolfsson discuss that CSAs can observe the choice behavior of the shoppers as they evaluate the listed alternatives from the search results and click on a specific product offer [Smith and Brynjolfsson 2001]. They show that such behavior can be analyzed using econometric models to reveal how shoppers respond to different aspects of product bundle like price, retailer brand-name, and shipping time. The merchants can use this information in their competitive price setting strategies. Yuan suggests that the current price dominated rank list may not help shoppers as they may have differing valuations for various non-price specific factors such as extended warranties, fast delivery times, loyalty benefits, diverse payment options, and vendor specific factors. In such cases, customized ranking model for the shoppers may become useful [Yuan 2002].

Prior researchers have also shown that CSAs can expand their domain by integrating models in order to facilitate purchase decision making under various shopping scenarios. Garfinkel et al develop an optimization model to offer the best deal to the shoppers when merchants offer bundle promotions [Garfinkel, Gopal et al. 2006]. Garfinkel et al show that the CSAs lack in providing comprehensive search cost solutions and by using an integer programming model, they can integrate promotion and product related search solutions [Garfinkel, Gopal et al. 2008]. They use integer programming based models to integrate promotions in the search results and also to offer product recommendations that maximize utilities of the shoppers.

User Interfaces: Even though CSAs have become popular, some shoppers do not use them because they find them difficult to understand. This effect is compounded by the fact that CSAs do not have an equivalent counterpart in the offline world [White 2000; Kocas 2003]. Hence, it is important that the CSAs deploy effective user interfaces to interact with the users. Majority of CSAs provide search box for the users to query their database and present search results in a table. Although it is important to provide multiple price quotes, if the information is not displayed properly then it becomes difficult to process that information [Haubl and Murray 2003]. On the one hand CSAs display side-by-side comparison of merchants and henceforth facilitate shoppers to select the most attractive option based on presented information [Trifts and Haubl 2003]. On the other hand, listing too many vendors for a product may not necessarily result in better sales for the later vendors due to the order effect [Xu and Kim 2008]. Hogarth and Einhorn define order effect as a consumer’s differential reaction to the options presented in different serial positions [Hogarth and Einhorn 1992]. The CSAs that list too many merchants in their search results increase the shoppers’ cognitive efforts and eventually may decrease the popularity of CSAs [Basartan 2001]. Although price may be the dominating factor on CSAs, in order to facilitate the shopper in obtaining the maximum utility out of their services, it is important for the CSAs to provide user interfaces with search and filtering tools to assist shoppers further [Xu and Kim 2008]. Prior researchers have observed that shoppers’ purchase decisions are affected by sorting options [Diehl 2005; Diehl and Zauberman 2005]. Sorting and parametric filtering based on multiple criteria, allows shoppers to rank the merchants based on their preferences and change the serial rank in which merchants appear on the screen. This may be advantageous to those merchants who compete based on non-price specific factors [Smith and Bryniolfsson 2001].

Users: One of the major benefits that the CSAs offer to the shoppers as well as merchants is that they can obtain pricing information of various competitors interactively, directly and in highly personalized manner (i.e. only for the specific product that the user is interested in) [Haubl, Dellaert et al. 2004]. The decision to select a merchant becomes complicated as the number of options increases. Shoppers typically simplify their purchase decision making process by reducing the available options to a more manageable set. This set is widely known as the consideration set [Narayana and Markin 1975]. In order to provide effective user specific personalization, it is important that the shoppers are provided effective tools in forming their consideration set. Majority of sorting and filtering tools allow shoppers some degree of personalization based on their own preferences. Majority of CSAs facilitate such limited personalization.

Yuan suggest that CSAs could provide better decision support to shoppers by adopting a differentiation strategy based on shoppers’ preferences [Yuan 2002]. In particular, he discusses that the data related to interaction history of the shoppers are necessary to form such personalization strategy. This interaction history data include, the product-retailer preferences, browsing patterns, time spent for browsing, and vendor inspection time. By using such data and econometric models, CSAs can learn the preferences of the shoppers and offer personalized recommendations to shoppers. Such data intensive user personalization strategies have been suggested by researchers. For example, methods are proposed to analyze the clickstream data for the adaptive Web design [Montgomery et al. 2004]. Likewise, Brynjolfsson et al. have suggested an econometric method for analyzing shoppers’ choices on CSAs [Brynjolfsson, Smith et al. 2007]. Prior researchers have discussed that shoppers can adopt three broad strategies when they use CSAs: maximizing expected value, price aversion, and brand seeking [Su 2007]. The CSAs can learn about shoppers’ preferred strategies and provide recommendation based on it. User personalization requires extensive data about the user-specific transactions. Although, the CSAs could have an access to such information, they have not fully exploited this opportunity. Majority of CSAs do not require shoppers to log-in for accessing search results. In the absence of any user specific data collection, it may not be possible for the CSAs to provide personalized services to the users.

4.3. Exploratory study

In order to link the academic research with the practical deployment of DSS, the features of a sample of CSAs are explored based on four core components of DSS. Top five CSAs (nextag.com, bizrate.com, shoplocal.com, shopzilla.com, and price grabber.com) are selected from eBizMBA.com's top 20 list in 2009[2]. Five sample items are randomly selected from the list of the top 100 selling items on Amazon.com and searched through these CSAs for this exploratory study.

Prior researchers have discussed the possibility of a misrepresentation of the pricing information due to merchant-dependent data extraction [Sadeddin, Serenko et al. 2007]**.** During our exploratory study, a quick look at the search results for digital cameras show the inconsistency between the actual price on a merchant's website, *buydig.com*, and the displayed price on a CSA, bizrate.com. Table 1 shows a list of data provided by the CSAs in our sample. It is clear from the table that while majority of CSAs have access to price quotes over the period of time, not many seem to be effectively using this data. As shown in table 1, only Nextag.com provides the trend for price, number of sellers, and leads by using time-invariant nature of data[3]. Thus, full potential of the data warehouse based storage technologies is not fully utilized by CSAs.

Table 1 provides overall summary of the data obtained from the CSAs. The data are organized into product, price, merchants, and promotion categories in line with the suggestion by prior researchers [Garfinkel, Gopal et al. 2008]. As shown in the table, CSAs provide basic product details and specifications, availability, user reviews and ratings, lowest price, merchant prices, tax, shipping, number of sellers, merchant name and logo, and merchant ratings and review data. These data elements clearly cover issues related to prices, online word of mouth, and vendor brand awareness as suggested by prior researchers [Smith and Brynjolfsson 2001; Xu and Kim 2008]. Prior researchers discuss that in order to provide comprehensive search costs based solutions to shoppers, CSAs should provide information about all four 'P's of marketing - products, price, merchants, and promotions [Garfinkel, Gopal et al. 2008]. Majority of CSAs provide the data support for the product, price, and merchant related information. However, very few (e.g. Bizrate.com) CSAs integrate the promotion related data in their results. *Bizrate.com* shows coupon information, expiry date, and coupon code for various merchants. As we can see from table 1, some CSAs use distinctive data which may be very useful for providing decision support to users. For example, *nextag.com* provides trend information regarding the number of sellers and price, which may help a user in understanding the product life cycle related issues and eventually decide the purchase timing. *Nextag.com* also provides information about sales leads (i.e. number of click-throughs) which inform the potential buyers about the interest of other shoppers and potential sellers about their stocking strategies and product listing opportunities. Likewise, *shoplocal.com* integrates information from multiple channels (i.e. online and B&M) by using weekly-flyers of B&M retailers. Table 1 shows that CSAs may not be using online analytical processing (OLAP) related tools effectively to provide comprehensive decision support by aggregating data. Likewise, majority of them do not consider sales promotions (e.g. coupons, rebates) [Wan and Peng 2010] or support B&M channels. Hence, they may provide suboptimal solution to shoppers' purchase decision making.

While CSAs have been using search-based and auction-based models for the operational purpose, the usage of analytical models was not evident during our exploratory study. Majority of the current CSAs provide search facilities to the shoppers to assist them in obtaining information that they are looking for. They also facilitate parametric search to provide further filtering facilities to the shoppers. For example, *bizrate.com* provides filtering facility for the digital camera by allowing users to select specific parameter values for megapixels, optical zoom, and brand. CSAs use automated auction-based models for listing and prioritizing merchants in the search results. Usually, for each product category, depending on the interest of merchants and shoppers, there is a minimum cost-per-click (CPC) bid amount specified. The merchants bid for listing their items for a specific product category and usually the search results are ranked based on the CPC bid amounts. For example, Appendix provides *nextag.com's* minimum CPC rates for various product categories. The entire mechanism for determining default ranking of merchants (i.e. featured merchants) uses auction-based models and is completely automated. CSAs can also use OLAP-based models for generating aggregated data effectively [Datta and Thomas 1999; Chaudhuri et al. 2001]. Majority of CSAs provide very basic aggregated information such as price range and minimum price. The CSAs like *nextag.com* provide more aggregated data such as mean, median, and average of historical price, number of

[2] eBizMBa.com provides periodical rankings of CSAs. These rankings are based on multiple criteria including Alexa website rankings, Google page rankings, and Compete monthly unique visitors.

[3] Other niche CSAs like, travel industry specific CSA, farecast.com, also provide detail price history trends.

sellers, and generated leads. Thus, although current generation of the CSAs deploy operational models extensively for performing their core functions, majority of them do not use analytical models to provide trends, recommendations, or comprehensive search support to the users.

Table 1: Data provided by CSAs for decision support[4]

CSA	**Data**
Nextag.com	Product: condition, details and specs, user reviews, availability, available since, trend for leads Price: lowest price, merchant prices, shipping, tax, price trend Merchants: no. of sellers, merchant name and logo, ratings, reviews, no. of sellers trend
Bizrate.com	Product: details and specs, availability Price: range of price, merchant prices Merchants: merchant name and logo, ratings, reviews Promotion: coupons (deals available)
Shoplocal.com	Product: details and specs, user reviews Price: range of price, merchant prices, shipping Merchants: online and B&M, merchant name and logo, Promotion: weekly flyers
Shopzilla.com	Product: details and specs, user reviews Price: lowest price, merchant prices, shipping, tax, Merchants: merchant name and logo, merchant ratings
Pricegrabber.com	Product: details and specs, user reviews, user ratings, expert reviews and ratings Price: lowest price, merchant prices, tax, shipping, security *('Mcafee secured'),* price alerts Merchants: no. of sellers.

All CSAs in our exploratory study use tabular format to display both price and non-price factors. Prior researchers discuss that listing of too many merchants in search results may lead towards the increase in the shoppers' cognitive efforts and eventually this may decrease the popularity of CSAs [Basartan 2001]. Table 2 shows that on and average a typical search on a CSA results in price quotes from at least 10 merchants. Moreover, overall price range and minimum price also vary across different CSAs. Although majority of CSAs provide search-based functions to reduce such information overload and cognitive efforts of shoppers, they do not use data visualization or dashboard approach effectively. In our study, only *nextag.com* uses charts to display various trends including price, number of sellers, and number of leads. As shown in figure 1, the travel-industry based CSA *farecast.com* uses grid-based interface to present data regarding departure date, arrival date, number of days of trip, and price. It further color-codes the cells in the grid in varying shades based on the price of the flight which significantly reduces the cognitive efforts of going through a large number of price quotes [Darlin 2006]. Such, data visualization may help in reducing the information overload further. However, it rarely exists in mainstream CSAs.

User specific personalization was not evident in our study. None of the CSAs explicitly require users to log in and hence do not have any user specific information. However, some CSAs like pricegrabber.com allow shoppers to specify their threshold price and send them alerts if the price of a product falls below that threshold.

[4] Underlined data are unique to specific CSAs.

Table 2: Summary of search results

Merchant	Search Results	Book (ISBN:9780316017923)	Canon Camera: SD880	Garmin GPS Nuvi 760	Logitech Webcam	Slumdog Millionaire
Nextag	Price Range ($)	15.49-31.48	244-299.00	191.98-215.99	37.19-60.94	NA
	Min. Price Vendor	HotBookSale	RedTagSavings	Tigerdirect	CompuVest	NA
	No. of Sellers	16	8	7	4	NA
Bizrate	Price Range	19-31.98	247.95-327.62	189.95-499.00	33.94-60.94	12.94-26.44
	Min. Price Vendor	Amazon MP	Amazon.com	Buy.com	Overstock	SmartSubs
	No. of Sellers	5	11	29	18	8
Shoplocal	Price Range	NA	246.88-253.88	235-237	33.24-60.94	13.02 -22.46
	Min. Price Vendor	NA	Buydig.com	Amazon MP	Compuvest	Amazon MP
	No. of Sellers	NA	4	10	3	4
Shopzilla	Price Range	19.57-31.98	255.25-299.99	199.99-499.99	39.95-60.94	12.94-21.56
	Min. Price Vendor	Overstock	Buy.com	Amazon	Amazon	SmartSubs
	No. of Sellers	7	12	32	18	10
Pricegrabber	Price Range	18.11-27.28	247.95-322.04	191.98-500.90	10.35-43.84	13.02-26.45
	Min. Price Vendor	Alibris	Amazon.com	TigerDirect	Insight	Amazon MP
	No. of Sellers	10	7	14	5	10

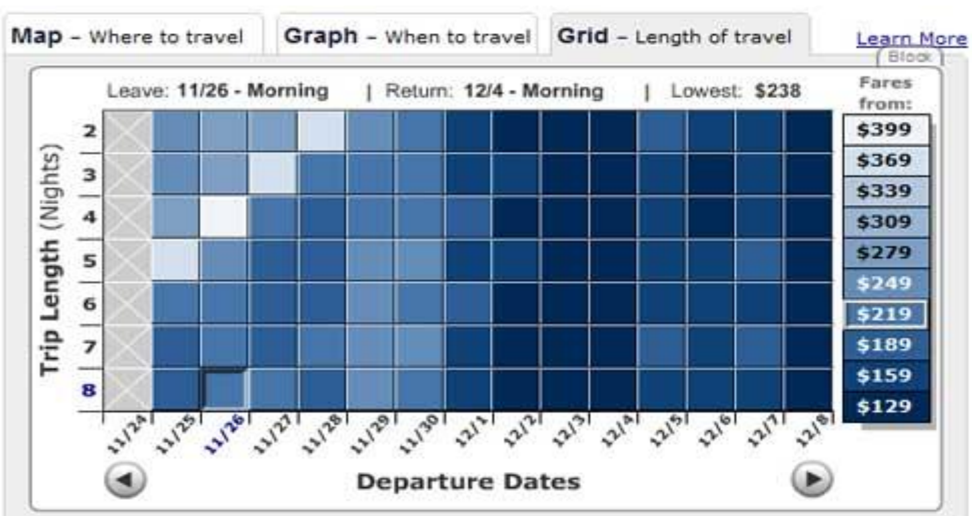

Figure 1: Data visualization on Farecast.com

5. Conclusion and research agenda

The objective of this work has been to analyze CSAs in the DSS context. To this extent, prior literature is synthesized based on four core components of DSS: data, models, user interfaces, and users. The survey of literature and exploratory study of some of the popular CSAs suggest that although CSAs have been using the core components of the DSS, there is a huge scope for further development and research in this field. Table 3 provides a brief summary of the DSS-related suggestions from the literature and current practices of the contemporary popular CSAs.

Table 3: CSA-based DSS features and the suggestions-based on prior research

DSS Components	**Suggestions based on prior-research**	**Features of contemporary CSAs**
Data	Product, price, promotion, merchants [Smith and Brynjolfsson 2001; Garfinkel, Gopal et al. 2008]	Product: details and specifications, user reviews and ratings, availability, availability since, trend for leads, editorial reviews and ratings Price: lowest price, merchant prices, shipping, tax, range of price, price trend, price alerts Promotion: limited information on coupons, and weekly flyers Merchants: no. of sellers, merchants name and logo, ratings and reviews, no. of seller*s* trend, online and B&M, security features
Models	Operational: data extraction through selective real time [Montgomery, Hosanagar et al. 2004] Analytical: Product bundling[Garfinkel, Gopal et al. 2006; Wan and Peng 2010], product recommendation [Garfinkel, Gopal et al. 2008], multiproduct purchase (e.g. Dvdpricesearch.com and Booksprice.com), price sensitivity and premium[Smith and Brynjolfsson 2001], price discrimination[Chen and Sudhir 2004], data mining and price prediction (e.g. Farecast.com), personalization[Yuan 2002]	Operational: data extraction and heuristics, auctions for merchants' bidding Analytical: some evidence of the usage of OLAP (aggregated trends)
User interfaces	Personalized ordered list[Menczer, Monge et al. 2002; Yuan 2002], multi-parameter ordered list[Xu and Kim 2008], data visualization (e.g. Farecast.com)	Sorting and filtering tools, tabular format data, basic trend charts
Users	recommendations[Garfinkel, Gopal et al. 2008], personalization[Menczer, Monge et al. 2002; Yuan 2002]	price alerts

DSS have been classified as data-centric or model-centric based on the extent to which the decision support relies on data or models [Bhargava and Downs 1996]. As can be seen from the table, contemporary CSAs are predominantly data centric. Contemporary CSAs predominantly use operational models and do not offer personalized solutions to consider the user specific heterogeneities. On the one hand the CSAs reduce the information overload and search costs by offering relevant information in a simple tabular format. On the other hand because of their wide-coverage of merchants, a better data-visualization based interfaces need to be developed to assist shoppers in exploring such comprehensive information. CSAs also have one-size-fits-all type of approach and do not offer shopper-specific personalization tools to consider user heterogeneities.

Research agenda

Based on comprehensive review of the academic literature in the fields of information systems, economics, decision support systems, and marketing, three distinct research fields are clearly identified. The first stream of research focuses on the design of the CSAs. In this stream, researchers analyze alternate data extraction and organization methods, efficient heuristics and models, effective and intuitive interfaces, and user-specific personalization methodologies in various contextual scenarios. The second stream of research predominantly deals with the economics of CSAs. Scholars investigate price dispersion, demand elasticity, economics of information, revenue model design, and search costs related issues. The third stream of research focuses on consumer behavior and marketing related issues. Researchers study the consumer behavior and purchase decision making at the CSA. For each of these streams, based on our DSS-focused survey and website study of a sample CSAs, a research agenda of issues is determined which requires examination by researchers and practitioners alike.

Design of CSAs: Current generation of CSAs is predominantly focused on a singular item, channel (i.e. online) and platform (i.e. computer). Shoppers' decision problem becomes more complex when they require evaluating options from multiple channels (e.g. catalog, online, and B&M) for multiple products (e.g. shopping cart comparison, bundle promotion) using multiple platforms (e.g. computers, mobile phones) . The design of CSAs for addressing such decision problem requires a robust data processing from multiple channels, flexible models for purchase decision optimization for the entire shopping cart, and contextual user-driven interfaces for mobile commerce. Majority of the popular CSAs are merchant-dependent where they receive price quotes from merchants at discrete time intervals. This makes the information on CSAs inconsistent with the actual price information on the merchant's website. In order to provide real time information to shoppers, the next generation of CSAs may use both merchant-dependent (e.g. XML data feeds) and merchant-independent (e.g. real time data collection) approach for data extraction. Further research is required to create more advanced alternative models wherein CSAs can be selectively searching for the price quotes on-the-fly [Montgomery, Hosanagar et al. 2004]. More importantly, existing data extraction methods do not allow CSAs to acquire information about frequent manufacturer or retailer promotions. In order to provide comprehensive and real time data support to shoppers, new extraction models need to be developed. The CSAs have an access to excellent price-demand related data and majority of them use advanced storage technologies based on data warehouses to store data. However, they have not been using mathematical models effectively to provide analytical decision support to shoppers. Development of OLAP and data mining based models to analyze purchasing patterns, preferences, and price trends is required in order to provide state-of-the art decision support to shoppers. Likewise, more research and development is required to present information using advanced data visualization technologies and to provide customized support to shoppers.

Economics of CSAs: The current revenue model of the majority of popular CSAs is merchant-driven. The CSAs provide price listing of merchants based on their revenue proposition. Such selection bias may present incorrect price dispersion related data to shoppers. This may increase the search costs of shoppers and require them to visit multiple CSAs or merchant websites in order to obtain an optimal solution to their purchasing decision problem. In-depth research is required to develop an alternate revenue-model for CSAs and provide complete price dispersion to shoppers. Majority of CSAs do not acquire the shopper specific data which restricts them from analyzing individual demand elasticity related information. Advanced research needs to be pursued in order to develop models to explore the price sensitivity at an individual level and offer personalized proactive product-merchant recommendation based on it.

Consumer behavior at CSAs: The CSAs occupy a key infomediary position between merchants and shoppers which endow them to analyze consumer behavior at both micro and macro level. However, CSAs neither acquire demographic data of shoppers, nor do they record shoppers' interactions including both queries and actions. Thus, they cannot effectively relate purchasing patterns to an individual's profile or provide personalized recommendations based on historical transactions. It is important that the next generation of CSAs maintain both the master demographic data and transaction data of shoppers at an individual level to learn their personal preferences and offer customized information, navigation, and interfaces. Such panel data can be applied to the econometric models in order to analyze the purchasing behavior of shoppers amidst heterogeneous merchants. Behavioral studies to analyze the multi-parameter ordering effect on a shopper's purchase decision also needs to be studied in order to analyze how do shoppers make decisions when faced with too many options.

While major focus of the current academic research in the CSA filed is on price dispersion, as shown above, there is an excellent potential for the research in improving the decision support aspect of the CSAs by developing alternate revenue models, advanced data extraction tools, robust analytical models, data-visualization based interfaces, user-specific personalization tools, plans to initiate empirical and experimental studies on consumer behavior.

Although this study provides a DSS-based survey and exploratory study of CSAs, this study has several limitations that point to future research directions in this area. First, this paper uses four-component framework of DSS in order to survey the literature. The marketing literature provides an outline of various stages of consumer purchase decision making. It will be interesting to explore the CSAs based on their decision support during each of these stages. Second, although the top five mainstream CSAs may constitute substantial market share, the exploratory study can be expanded to more CSAs to provide a comprehensive coverage of CSAs. Third, this survey is predominantly-focused on the merchant-dependent CSAs, other CSA-based models such as merchant-independent and embedded CSAs [Wan, Menon et al. 2007] needs to be analyzed and compared.

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APPENDIX

Nextag.com's Minimum CPC Rates for various product categories:

Computers	($)	Baby	($)	Other Products	($)
Accessories	0.6	Baby Carriers	0.35	Automotive	0.2
Camera Lenses	0.7	Car Seats	0.35	Books	0.15
Printer Supplies	1	Cribs	0.35	Collectibles & Art	0.3
Cables & Adapters	0.7	Strollers	0.35	Event Tickets	0.1
CPU, Chassis & Components	0.7	Others	0.25	Flowers & Plants	0.3
Desktops Graphics	0.7			Food & Wine	0.2
Handhelds/PDA	0.7	Accessories	0.25	Gift Cards	0.3
Input Devices	0.7	Children	0.25	Gifts	0.25
Monitors	0.7	Handbags & Wallets	0.25	Health & Beauty	0.5
Network & Communications	0.7	Jewelry & Watches	0.5	Fragrances	0.5
Notebooks	0.7	Watches	0.6	Vitamins & Nutrition	0.3
Power Protection & Supplies	0.7	Men	0.3	Internet Services	0.18
Printers	0.7	Shoes	0.3	Magazines	0.15
RAM & Memory Upgrades	0.7	Kids' Shoes	0.3	Movies	0.15
Scanners	0.7	Men's Shoes	0.35	Music	0.15
Servers, Terminals & Thin Clients	0.7	Women's Shoes	0.35	Musical Instruments	0.15
Service Agreements	0.7	Sunglasses	0.3	Office Products	0.5
Software	0.7	Women	0.3	Multimedia Projectors	1
Sound Cards & Multimedia	0.7	Undergarments	0.25	Office Equipment	0.7
Storage Devices	0.7	Others	0.25	Sports & Outdoors	0.3
Others Electronics	0.7			Fitness Equipment	0.3
Electronics	($)	Home & Garden	($)	Supplies QuickFind	0.4
Accessories	0.5	Bed & Bath	0.3	Toys	0.25
Camera Lenses	0.7	Furnishings	0.35	Video Games	0.25
Binoculars & Telescopes	0.7	Furniture	0.3	Accessories	0.35
Camcorders Car Audio & Video	0.7	Home Improvement	0.35	Consoles	0.35
Digital Cameras	0.7	Kitchen	0.35	Others	0.25
Film Cameras	0.7	Lawn & Garden	0.35	Coupon	($)
GPS Systems	0.8	Major Appliances	0.3	Clothing & Accessories Deals	0.2
Home Audio	0.7	Pets	0.2	Computer Deals	0.5
Speakers Phones & Communications	0.7	Small Appliances	0.6	Electronics Deals	0.5
Portable Audio & Video	0.7	Others	0.3	Home & Garden Deals	0.2
Storage Media	0.7	Travel	($)	Services Deals Travel Deals	0.1
Televisions	1	Airfare & Hotel	0.4	Travel Deals	0.5
Plasma & LCD	1	Car Rentals	0.30 0.40	Others	0.05
Video Components	0.7	Cruise	0.4	Services	($)
		Flights	0.2	Credit Card	1
		Hotels	1	Home Equity A	0.5
		Others	0.5	Home Purchase A	0.5
				Home Purchase B	0.5
				Homes and Real Estate	0.01