# Online shopping bots for electronic commerce: The comparison of functionality and performance

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**Abstract:** Shopping bots are software applications that assist consumers with online comparison-shopping by searching for, identifying, and comparing products offered by numerous e-tailers. This paper examines the output of nine comprehensive shopping bots that were employed to conduct multiple searches for forty books, twenty CDs, and twenty DVDs. The results produced by each bot were analyzed in order to determine bot effectiveness based on accuracy, consistency, and repeatability of recommendations, using product price as a key measure. It was concluded that there is no best shopping bot available, most bots offer very limited product information to the end users, and all bots often present inaccurate information in terms of the actual product price or product availability. Based on the findings, several recommendations for shopping bot developers and researchers are presented.

**Keywords:** electronic commerce; intelligent agents; e-business; shopping bots; functionality; performance; Internet; price.

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## 1 Introduction

### *1.1 What are shopping bots?*

Shopping bots are "automated tools that allow customers to easily search for prices and product characteristics from online retailers" [1, p. 446]. They are available on the Internet and act as electronic commerce search engines. Bots accept user queries, visit e-shops or websites of online merchants that may have a specific product, retrieve search results, and present them in a consolidated and compact format for visual comparison. The purpose of this paper is to examine the functionality and performance of various shopping bots (or price comparison engines) for electronic commerce.

There are various shopping bot services. In general, they can be divided into two types: server-based and client-based solutions. A *server-based* shopping bot performs price comparison on a Web server. Some examples include Bestbookbuys.com, Pricewatch.com, and mySimon.com. For a *client-based* bot, a special software application needs to be installed on the client-side. This system can be configured to check specific item prices from known vendors or search engines on a regular basis. Some examples include Copernic Shopper[1] and Best Price[2] [2].

Technically, there are three ways to provide shopping bot services: a centralized database, broker agents and mobile agents. In the *centralized database approach*, each shopping bot has its own product information database. Sellers submit their offerings and update the database regularly, either manually or automatically. Essentially, the bot provides advertising services for the sellers.

In the *broker agent approach*, shopping bots are used to extract product information from different sellers' web sites. *Mobile agents* can be utilized to visit each seller's website to compare the price of the product of interest. Besides searching, a mobile agent

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1 www.copernic.com
2 www.bestprice.com

can in fact be employed to complete a purchase which is the last step in the buying process [2].

### *1.2 Motivation for the development of shopping bots*

A theoretical framework that leads to the development of shopping bots can be found in the economics of information theory, where Stigler [3] argued that consumers who value time will stop searching when the marginal benefits of search no longer outweigh the marginal search costs. Hence, the usage of a shopping bot is not limited to simply typing in a few keywords and waiting for the results. Consumers need to decide how the information generated by a bot adds to the entire purchase decision-making process.

To be effective, time spent searching with shopping bots needs to be minimized. This is particularly important since the use of a shopping bot is only one stage in the product acquisition process. Peterson, Balasbramanian, & Bronnenberg [4] emphasize that for some categories of goods, consumers are likely to search both the Internet and conventional retailing channels. The theoretical framework mentioned above was the driver for the early stages of shopping bots design and implementation and continues to fuel the efforts of improving the performance and functionality of shopping bots.

In the past, shopping bots were often referred to as agents, intelligent agents, software agents or intelligent assistants. In this paper, they are treated as regular software-based applications. It is noted that a discussion of whether shopping bots actually belong to the field of intelligent agents is out of the scope of this project. As such, this study concentrates on the performance aspects of this technology rather than on its theoretical or philosophical issues.

### *1.3 History of shopping bots*

As early as 1995, researchers envisioned shopping bots as a solution for finding products under the best terms from online vendors when price was typically the most important feature [5]. A shopping agent queries multiple sites on behalf of a shopper to gather pricing and other information on products and services. Client-based shopping bots that appeared in the beginning of 1997 achieved that by allowing consumers to comparison-shop online without actually visiting merchants' sites to locate best prices [6].

The first shopping agent (BargainFinder) was developed by the consulting firm Andersen Consulting in 1995 [7]. It let users compare prices of music CDs from Internet stores. However, some retailers blocked access because they did not want to compete purely on price, and BargainFinder ceased operations. PersonaLogic, another comparison-shopping bot, let users create personal profiles to describe their preferences. This approach allowed the bot to identify products with features that users considered most important. However, vendors had to provide interfaces that explicitly disclosed product features so that PersonaLogic could match them with user profiles. AOL (America Online) acquired PersonaLogic in 1998, and the technology disappeared soon after that.

Ringo was a bot that recommended entertainment products, such as CDs and movies, on the basis of collaborative filtering by using opinions of like-minded users [8]. Collaborative filtering implies making automatic predictions (filtering) about the interests of a user by collecting preference information from many users (collaborating). An underlying assumption of collaborative filtering approach is that those who agreed in the past tend to agree again in the future. For example, a collaborative filtering or recommendation system for music preferences could make predictions about which music a user should like given a partial list of that user's tried before (likes or dislikes). Such predictions are specific to the person, but use information gleaned from many users. This differs from a more simple approach of giving an average (non-specific) score for each item of interest, for example based on its number of votes. This became one of the earliest commercialized bot technologies when it evolved into FireFly [9]. Microsoft acquired FireFly Network Inc. in 1998, and the FireFly bot ceased operation shortly thereafter. However, collaborative filtering has become a common technique nowadays; for example large commercial vendors such as Amazon use it, although in simplified ways.

ShopBot, another price comparison engine, could submit queries to e-commerce sites and interpret the resulting hits to identify lowest-price items [10]. ShopBot automated the building of “wrappers” to parse semi-structured HTML documents and extract features, such as product descriptions and prices. The process would entail wrapping treatments learners (programs used to find rules that change the expected class distribution compared to some baseline) in a preprocessor that would search to make subsets from the current set of attributes. The attribute subset would continue to grow until the accuracy of the model was no longer more accurate. Parsing transforms input text into a data structure, usually a tree, which is suitable for later processing and which captures the implied hierarchy of the input. The overall method when applied to data sets from e-vendors’ websites would yield an HTML documents with the specified attribute set extracted from such website. Despite the usage of wrappers, the ShopBot technology’s fate was similar to those of PersonaLogic and FireFly. Excite acquired and commercialized it under the name Jango but soon replaced it with a biased vendor-driven agent [9].

Tete@Tete was a bot that integrated product brokering, merchant brokering, and negotiation [11]. A start-up called Frictionless Commerce applied the technology to business-to-business rather than to business-to-customer markets. Most of the comparison-shopping agents available to consumers such as MySimon, DealTime and RoboShopper, present results only from partner companies who pay service subscription fees.

Most current business models are based on vendor rather than buyer revenue, because users are reluctant to pay fees for these services. However, a vendor-based revenue model still produces hidden costs such as higher prices, limited choices, and poor service. In this context, the established vendors’ reluctance to shopping bots is certainly understandable [9].

### *1.4 Current state of research on shopping bots*

Based on a comprehensive review of academic literature in the fields of Management Information Systems, Human-Computer Interaction and Computer Science, three distinct approaches to study shopping bots were identified. The *first line of research* focuses on the engineering of technical design and functionality aspects of shopping bots. As such, the scholars investigate various design specifics and technical algorithms that can be developed and utilized to enhance shopping bot performance. Such enhancement would yield better functioning systems with increased accuracy of information gathered from vendors, and a more adaptive and customized shopping assistance for online consumers [9]. Other aspects of the engineering approach are the design and performance assessment of other models of shopping bots such as mobile shopping bots and the investigation of the effectiveness of their functionality [2].

The *second research approach* focuses on the economic effects of bots. In this type of research, academics analyze the impact of shopping bots on various economic problems, such as price dispersion (defined as the distribution of prices across sellers of the same item, standardized for the item's characteristics) in the online environment [12], economics of information theory [3, 13], value of information in online markets [14], and price range and consumer intentions [12].

The *final approach* to shopping bots research is the impact they have on marketing issues, such as consumers response to the presence of shopping bot services [1]. Researchers explore the role of service quality as an important product attribute even for otherwise homogeneous goods [15]. The influence of shopping bots on consumer research behavior [16] and many similar marketing issues related to shopping bots are also studied.

Overall, the area of research presented above is in its embryonic stage of development. Most documented works offer theoretical discussions and conceptual overviews of the field, or the technological solutions for bot implementations. Based on an extensive and exhaustive search of all major indexes, journals, and online resources conducted by the authors, there have been only a few attempts to study the performance and functionality of shopping bots from the end-use perspective.

Even though the popularity of shopping bots has been continuously growing, there have been very few attempts to empirically evaluate their performance. Such evaluation would be the true test of their abilities at gathering unbiased and thorough product-related information and presenting it in a useful fashion that would reduce search costs and facilitate an efficient decision making process. This study suggests and attempts to answer a number of research questions that have not been covered before through a quantitative approach.

The expected contribution of this paper is two-fold. First, this will be one of the first documented attempts to empirically investigate the performance of shopping bots. Second, based on the findings, a number of suggestions for shopping bot service providers, electronic commerce companies utilizing this technology, and online consumers will be provided. Unfortunately, no such guidelines are presently available. The following section offers more detail on the theoretical background and research questions.

## 2 Theoretical background and research questions

There is a general consensus that a consumer buying process can be divided into three phases, namely searching, comparing and executing [2]. For consumers, online shopping may greatly facilitate the collection of item-related information and price comparison. Online shoppers may adopt a number of strategies when looking for a product. The most straightforward approach is to visit various vendor websites; for each one, a person searches for a particular product.

This simple approach has several drawbacks. First, because no single site caters to all shopping needs, a user's search time increases for each new product category. Second, getting acquainted with individual non-standard vendor interfaces slows browsing and hinders impulse shopping. Third, this approach likely favours only the largest vendors (e.g., because of name-branding), which reduces the market's efficiency by providing fewer competitive choices to consumers [9].

There are several widely employed online tools that assist shoppers. For example, some vendors allow individuals to sign up to receive price alerts that notify them when a product's price changes or falls below a specified amount. Some of these services require shoppers to fill out lengthy surveys, and most of the websites offer little or no personalization. Even though it is possible to offer personalized shopping experience by creating user profiles, this shopping approach has attracted much criticism because it threatens people's privacy [9].

Another option involves the compilation of voluntary user ratings and reviews of vendors and products. Such recommendation systems might reduce the marketplace's size and introduce bias, because obtaining a sufficient number of ratings for every vendor and controlling the sources' reliability are difficult to achieve for a single shopper.

Overall, shopping bots offer a good alternative to further automate the search process that has been gradually gaining recognition among online shoppers. Specifically, shopping bots, or price comparison engines, may alleviate some of the shortcomings of the solutions above. Several theories exploring the impact of shopping bots on various aspects of electronic commerce were proposed since the inception of this technology. For example, some of these theories discussed economic factors such as online price dispersion, and marketing factors such as marketing mix needed by retailers in response to shopping bots. Other theories addressed consumer behaviour such as people's response to shopping bots' information and services. While such research addressed some of these issues that have presented in the previous section of this paper, many questions remain unanswered or partially covered, and further exploration is needed.

It follows from the extant literature that the degree of price dispersion and consumers' reactions to price dispersion are a very important investigation area [4]. Managers must be aware of macro forces (such as price dispersion) to deal effectively with variables within their control (such as pricing). Many conjectures have been made in the business literature about a lower degree of price dispersion that should emerge due to the Internet [12]. Since Internet presence has virtually become a necessity [17], most managers have to deal with Internet pricing issues at some point – and thus with the forces of price dispersion. Therefore, various effects of price dispersion, including the average item price, number of competitors in the marketplace selling a specific product (or a number of vendors reported by the shopping bot), and retailer quality need to be examined carefully.

In one of the first attempts to empirically investigate the functionality of shopping bots, Rowley [18] compared search facilities and outputs across ten different shopping bots using three recent best selling books as a product group. She found that there was a significant variability in the search facilities and search outputs among different shopping bots. Most bots offered searches by title, author, and ISBN. For the most part, search mechanisms were found to be rudimentary. Searches on title fragments and parts of author names produced long lists of items that led to information overload.

Rowley's use of search facilities and the accuracy of search outcomes in terms of book title and author name provided a measure to compare the functionality (effectiveness or accuracy) of any shopping bot. However, to further our knowledge and understanding of the functionality of shopping bots, other indicators can be used as forms of measurement to asses the performance of a shopping bot and allow comparing it with other bots. Since price dispersion results can be used as a performance indicator, the following research question is suggested:

*Research Question 1: Do different shopping bots produce similar price dispersion results (high, low and average price) for identical product searches?*

Early electronic commerce studies hypothesized that online retailing would spiral into a never-ending price war [15], while more recent projects discovered that price is not the only factor because many customers tend to pay higher prices to superior quality online retailers that they trust. This explains why more than 50% of the dollars spent online go to the top 30 retailers [19] and points out that price alone is not the only dimension of competition in the online retail environment. For example, Collier and Bienstock [20] argue that product delivery has a very strong influence on customers' satisfaction and future purchase intentions.

Rowley [18] found that the various outputs of shopping bots varied considerably; some offered only item price, whereas others showed delivery and shipping arrangements. Both delivery options and price can be influential factors in consumer purchase decisions. Rowley concluded that shopping bots are likely to play a useful role in profiling the e-market place in future, but their functionality should be improved.

Users require various output information generated by shopping bots. These include variations in shipping and handling information, customers' feedback on vendors, product reviews, tax charges, delivery time, product views, and return policies. Therefore, it follows that another measure of a shopping bot overall functionality can be the provision of supplementary information that can aid users in making a rational decision about a purchase:

*Research Question 2: Do different shopping bots produce similar supplementary information, such as shipping and handling, customers' feedback on vendors(vendors' reviews), product reviews, tax charges, delivery time, product views (i.e., pictures), and return policies?*

Accuracy, defined as information integrity, is another factor that may dramatically influence the usefulness and future adoption of shopping bots. For instance, if there is a difference between the product price presented by a shopping bot and the actual price that the vendor charges the purchaser, it is unlikely that this user will ever utilize this specific bot, or even any other bots, in future. To further enhance an understanding of bots functionality, another measure can be employed as an indicator of performance. As such, the integrity of the information provided by the bot is believed to be highly important, and a third research question is suggested:

*Research Question 3: How accurate is the information and recommendations provided by shopping bots? (i.e., is the item in fact available from each reported online vendor for the quoted price?)*

The last, but not the least measure that can be useful to bots' users is the number of options it provides in terms of the number of potential vendors who sell the required product, allowing for a wider range of price/product/supplementary information available to customers. Hence, e-merchant coverage may be a very useful measure of bot functionality, and the following research question is suggested:

*Research Question 4: Do different shopping bots produce similar e-merchant coverage results?*

## 3 Methodology and results

### *3.1 Experiment description*

In order to examine the effectiveness of shopping bots as shopping tools, an experiment was conducted. Nine shopping bots were randomly selected from an exhaustive list available at the Web site *www.botspot.com* after excluding specialized bots. The intention of this study was to focus on general shopping bots with wide product coverage, therefore bots that specialized in particular product groupings were excluded from consideration. All of the selected bots were server-based solutions.

The following shopping bots were randomly selected: ActiveShopper.com, BizRate.com, DealTime.com, Dulance.com[1], MySimon.com, NexTag.com, PriceGrabber.com, PriceScan.com, and Shopping.com. For products, 40 books were randomly selected from the New York Best Seller list covering four different topics: fiction (entertainment), non-fiction (general interest), business, and children books. Twenty CDs and twenty DVDs were also randomly selected from the New York Best Seller list.

All products were searched either by ISBN, ASIN, or UPC number. Only new items were considered. This enabled the explicit identification of identical products for searching using each shopping bot. This prevented the need to utilize keyword and title searches provided by the shopping bot search facilities, which was not included in the scope of this study. The following sub-sections outline the results.

### *3.2 Price comparison*

To answer the first research question of whether different shopping bots produce similar price dispersion results (high, low and average price) for identical product searches, the high, low and average prices of products were compared using ANOVA. This data analysis technique was chosen because it allows keeping the significance level constant

[1] It is noted that the service by Dulance.com was discontinued soon after the completion of this study.

when analyzing data produced by different bots. In the present case, the employment of MANOVA was not recommended because of variable interdependency (i.e., average price is influenced by both high and low prices).

The overall goal was to test price dispersion of the shopping bots under investigation for three sets of products: 1) books; 2) DVDs; and 3) CDs. Only those products that were actually available on the vendor's website were considered. Table 1 offers the results. All values statistically significant at the 0.001 level indicate that there are differences in this product category for a specific price (i.e., high, low or average). For example, in terms of an average price, a difference for CDs but not for books and DVDs was observed.

**Table 1** Price comparison

| | *High Price* | | *Low Price* | | *Average Price* | |
|---|---|---|---|---|---|---|
| | *F-value* | *P-value* | *F-value* | *P-value* | *F-value* | *P-value* |
| ***Books (n=40)*** | .273(8;346) | ns | 1.590(8;346) | ns | .128(8;346) | ns |
| ***DVDs (n=20)*** | 6.598(8;168) | < .001 | 12.202(8;168) | < .001 | 1.258(8;168) | ns |
| ***CDs (n=20)*** | 14.423(8;161) | < .001 | 16.997(8;161) | < .001 | 26.940(8;161) | < .001 |

### *3.3 Supplementary information comparison*

The goal of the second research question was to study the comprehensiveness of supplementary product information such as shipping and handling, customers' feedback on vendors, product reviews, tax charges, delivery time, product views (i.e., pictures), and return policies. To answer this question, each shopping bot was individually analyzed. Table 2 offers the results.

**Table 2** Supplementary information

| | *Shipping/ handling* | *Vendor Reviews* | *Product Reviews* | *Taxes* | *Delivery Time* | *Product Views* | *Return Policy* |
|---|---|---|---|---|---|---|---|
| ActiveShopper | yes | yes | no | no | no | yes | no |
| BizRate | yes | yes | yes | yes | no | yes | no |
| DealTime | yes | yes | no | no | no | yes | no |
| Dulance | no | no | no | no | no | no | no |
| MySimon | yes | yes | yes | no | no | yes | no |
| NexTag | yes | yes | yes | yes | no | yes | no |
| PriceGrabber | yes | yes | yes | yes | no | yes | no |
| PriceScan | no | yes | yes | no | yes | no | no |
| Shopping | yes | yes | yes | yes | no | yes | no |

Based on the findings, it is concluded that no shopping bot offers comprehensive supplementary information. As such, none of them informed users about product return policies. Only one (PriceScan) offered delivery timeline, and four bots (BizRate, NexTag, PriceGrabber, and Shopping) either calculated or allowed people to calculate tax charges. At the same time, a majority of bots had shipping/handling information, product views, and customer reviews on vendors.

### *3.4 Information accuracy and online vendor coverage*

The third research question concentrated on the accuracy of obtained results. To investigate this issue, each case when the advertised product was not actually available on the vendor’s website was counted. For example, after obtaining a search list for a particular book, the researchers visited each vendor to verify whether the book was actually available for purchase. The first row of Table 3 portrays the accuracy of each shopping bot investigated by listing the number of times a product was not found on a vendor’s website.

The fourth research question focused on e-merchant coverage. In order to answer this question, price searches were performed, using each of the nine shopping bots, for each of the eighty items. Each time a new, unique vendor was encountered in a search result, it was assigned a unique vendor code to be used throughout the experiment. In the process of conducting these searches, the data was compiled in tables that indicated, for each item searched, each of the vendors returned by each shopping bot. These data were summarized to indicate the average number of unique vendors returned by each shopping bot. Table 3 offers the findings. As such, it presents the number of times each product was not available, the average number of unique vendors, and their ratio.

**Table 3** Information accuracy and online vendor coverage

| | *ActiveShopper* | *BizRate* | *DealTime* | *Dulance* | *MySimon* | *NexTag* | *PriceGrabber* | *PriceScan* | *Shopping* |
|---|---|---|---|---|---|---|---|---|---|
| Product not available | 8 | 11 | 12 | 20 | 14 | 6 | 19 | 43 | 9 |
| Avg. # of unique vendors | 3.10 | 8.99 | 3.21 | 8.95 | 4.23 | 4.00 | 9.54 | 11.51 | 3.39 |
| Ratio | 2.58 | 1.22 | 3.74 | 2.23 | 3.31 | 1.50 | 1.99 | 3.74 | 2.65 |

## 4 Discussion, conclusions, and directions for future research

### *4.1 Answers to research questions*

The overall purpose of this study was to empirically investigate the functionality and performance of online shopping bots. For this, an empirical experiment was conducted. Based on the extant literature, four research questions were proposed. Three categories of products were selected, and 80 items were randomly chosen: books (n=40), DVDs (n=20) and CDs (n=20). Web-based searches on nine shopping bots were performed during one day.

The goal of the first research question was to analyze price dispersion of shopping bots. There are three points that need to be addressed. First, no statistically significant differences were discovered for book prices. This implies that the overall high, low, and average prices are similar for the nine bots under investigation. At the same time, a visual inspection of the dataset demonstrates that, in each case, there was at least one price that was dramatically lower than those of other bots. This reveals that online shoppers may potentially find a real bargain for a specific product if they utilize each bot and compare the results.

Second, in the case of DVDs, significant differences in shopping bot performance were found for high and low prices; BizRate and PriceGrabber had the lowest prices, and PriceScan had the highest ones. Third, for CDs, high, low and average prices were different; for example, NexTag was the lowest price leader. Based on these observations, it is suggested that, in general, there is no ‘best’ or ‘parsimonious’ shopping bot in terms of price advantage. Indeed, the performance of shopping bots depends on the overall product type as well as on a particular product.

Therefore, it is argued that in order to locate the best deal on the Internet, shoppers should obtain information from a variety of bots. A possible alternative for shopping bot vendors may be to develop a meta-shopping bot that would work similar to meta-search engines. As such, a meta-bot would obtain product information from several shopping bots, summarize it, and present it to the user.

The objective of the second research question was to analyze supplementary information offered by shopping bots. The analysis indicated that no shopping bot provided comprehensive supplemental information of this nature, and in general, supplied information was only found to be satisfactory. Breitenbach and Van Doren [21] suggest that online price comparisons represent a very complex process. As such, in the intensely competitive environment of the global e-commerce marketplace, e-merchants will attempt to differentiate themselves by offering additional benefit to their consumers, such as favourable delivery options, attractive return arrangements, flexible payment options, and superior service.

It is suggested that these factors affect the consumer's overall satisfaction and perception of the value obtained through their purchase. If these criteria are important to consumers and are likely to influence their purchase decisions, then it would likely substantially benefit the user if this nature of supplemental information were to be supplied by shopping bots. It is therefore concluded that there is some potential to improve the thoroughness and nature of information provided by shopping bots, thereby further reducing search costs for individual consumers and enhancing their shopping experiences.

The purpose of the third research question was to investigate the accuracy of information, and the goal of the fourth question was to study e-vendor coverage of shopping bots. In terms of information accuracy, bots varied in their degree of information truthfulness. NexTag and PriceScan offered the lowest and highest number of products that were not actually available on the vendors' websites respectively. All other bots presented approximately the same number of incorrect displays. This measure of information accuracy is likely to be a critical criterion to online consumers in their assessment of various shopping bots, and might lead to long lasting implications in terms of consumers' loyalty to certain bots. In future, higher rates of bots usage may make e-vendors offer more supplemental information to further reduce search costs for online consumers and enhance their shopping experiences.

With respect to e-vendor coverage, ActiveShopper and PriceScan retrieved and presented product information from the lowest and highest number of sellers respectively. A major finding is a relatively consistent ratio of item unavailability and the average number of sellers (see Table 3). It demonstrates that there is a positive relationship between the number of errors and the number of e-vendors.

### *4.2 Implications*

The overall purpose of electronic commerce shopping bots is to extract accurate and reliable information on the combination of price/product/supplementary information that would eventually direct the potential shopper to the vendor's website. In this study, several key issues were discovered that may be of interest to shopping bot developers, e-vendors, and online shoppers.

First, Internet users should know that currently no single shopping bot can be viewed as the best, most comprehensive, or most price effective. In fact, depending on the nature of a specific product, each shopping bot may be more or less useful in terms of locating the best deal on the Internet. Therefore, individuals looking for a specific product online should query as many bots as possible to locate the best deal.

Second, a meta-shopping bot may be developed whose workings would be similar to those of meta-search engines. A meta-shopping bot would query a variety of independent shopping bots and present this information in the most effective and efficient way to the user. This would dramatically reduce user workload and increased the probability of locating the best deal online. At the same time, it is possible that independent bot owners may potentially oppose supplying information to such meta-search engines since this may undermine their business models. Therefore, practitioners may investigate the technological underpinnings of meta-bots, and researchers may study the viability of such business concepts.

Third, the quality of supplementary information provided by shopping bots is hardly satisfactory. For example, only one bot presented delivery options, and none described product return policies. At the same time, online shoppers do require additional product information regarding shipping and handling, customers' feedback on vendors, product reviews, tax charges, delivery time, product views, and return policies. It is suggested that bot service providers may dramatically differentiate themselves from their competitors if they find ways to offer such information to the users.

Fourth, no shopping bot investigated in this project presents perfectly accurate information in terms of product availability. It was observed that as the number of unique vendors increases, so does the number of false products (i.e., when the advertised product is not actually available at this price from the vendor). Therefore, to maximize the correctness of shopping bot information, a number of vendors may need to be minimized. This suggestion, however, may be too difficult to implement since the elimination of some vendors may potentially minimize the market coverage. One short-term solution is to review the accuracy of information presented by each e-vendor and to eliminate those with the highest amount of incorrect product or price displays. As such, it is argued that information correctness is the most vital issue. If bots continue displaying a high proportion of incorrect offerings, many shoppers will soon realize that they are not always getting the best deal, develop a high degree of distrust in this technology, and eventually stop utilizing shopping bots.

### *4.3 Conclusions and directions for future research*

Despite its innovativeness and potential, this study had certain limitations that, if considered in future research, will add to the validity of the findings, and possibly further our knowledge in this area. *First*, for this experiment, data were collected at one particular point in time. It would be interesting to test whether this study's findings hold true if a longitudinal experiment is conducted. *Second*, only three product categories, such as books, CDs and DVDs, were utilized in this project.

The body of knowledge would benefit if future researchers replicate this study by using other products that are also frequently sold online. Such an experiment may determine more differences in the functionality and performance of shopping bots across product groups. *Third*, the nine bots investigated in this project were comprehensive because they targeted all kinds of products. In contrast, specialized shopping bots concentrate on only a few product categories. At the same time, little is known about their performance and functionality. *Finally*, this project focused on shopping bots that support the English language only, but there may be shopping bots employed in other languages. The performance and functionality of those bots should also be investigated. Despite these shortcomings, it is believed that none of the limitations above is crucial, and that this study was successful.

Shopping bots are a novel technology that has been available to electronic commerce customers for only a few years. At the same time, it has a great potential to empower online shoppers by helping them locate the best deals on the Internet. Whether shopping bots secure a position in the electronic marketplace depends on the companies developing and deploying this technology. It is strongly recommended that researchers continue investigating the performance and functionality aspects of shopping bots and practitioners utilize their findings to deliver the best technology to the end users.

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## References and Notes

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