Investigating the functionality and performance of online shopping bots for electronic commerce: a follow-up study

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Abstract: Shopping bots are automated software applications that allow consumers to easily search for and compare product prices from online retailers. In a previous project, researchers investigated the functionality and performance of e-commerce shopping bots. The purpose of this project is to test the temporal stability of their findings two years later. Both studies concur that no 'best' shopping bot exists, and all bots often present inaccurate product price and availability information. A positive relationship between the amount of incorrect product information and the number of online vendors was confirmed. Supplemental information provided to users still remains deficient. Differences in product prices were observed.

Keywords: e-commerce; electronic commerce; electronic business; shopping bot; shopbot; functionality; performance; price.

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1 Introduction

Shopping bots for electronic commerce (e-commerce) are software systems that facilitate effective and efficient product price comparison from online retailers (Smith, 2002; Serenko and Detlor, 2004; Serenko et al., 2007). They are available in the internet and act as e-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. Overall, they offer tremendous benefits for online shoppers, who may potentially locate lower prices, and for online vendors, who may get more exposure for their brands, promote their websites and increase sales.

A recent study by Sadeddin et al. (2007) compared the functionality and performance of online shopping bots and presented a number of conclusions. First, no significant book price difference among nine examined bots was found. However, for CDs and DVDs, several bots consistently delivered lower prices. Second, it was suggested that most bots do not offer sufficient supplementary information, such as shipping, handling, vendor reviews, product feedback, taxes, estimated delivery time, product views and return policies. Third, all bots varied in their extent of information truthfulness since they all presented approximately the same amount of incorrect information, such as wrong prices. Fourth, a positive relationship between the number of errors and number of online vendors was observed. Overall, it was concluded that, at the date of the experiment, there was no shopping bot that performed the best, and all bots offered limited and often incorrect information about product price and availability. The authors stated that shopping bots are in an emerging stage of development and more research is needed to understand their functionality, performance and potential impact.

Electronic commerce is a new and continuously changing area. Since its birth just over 10 years ago, a variety of business models, systems and applications have appeared. Shopping bots are also a novel and dynamically changing technology. Since their inception, the workings of shopping bots have been continuously modified, new vendor relationships have been established, and new forms of bots' usage have been offered. Therefore, it may be assumed that the previous conclusions about the functionality and performance of shopping bots may change over time. Has this technology actually evolved? Is it still true that to locate the best deal online, people should utilise all available shopping bots? Do the contemporary bots offer more comprehensive supplementary information? Are bots more reliable now than two years ago? The answers are yet unknown. Therefore, the purpose of this project is to test the previous findings by Sadeddin et al. (2007) to observe possible changes in the performance and functionality of shopping bots two years later. This study employs the same approach and methodology; however, it is more comprehensive, comparing the functionality and performance of 16 shopping bots rather than nine.

The expected contribution is that, given the accelerating pace of shopping bot technology development, it is currently unknown how much progress the industry has made and whether the previous project's findings are still applicable. Online shoppers may want to know about the best ways to utilise e-commerce shopping bots. Bot developers need to know about the overall state of this technology. Online merchants may benefit by knowing whether the bots are currently trustworthy that may affect their future adoption. For example, offering products through a bot that often returns incorrect prices may dramatically damage the brand and reputation of some online sellers.

The rest of this paper is structured as follows. Section 2 presents theoretical background and study's research questions. Section 3 describes methodology and outlines the results. The last section discusses the findings, outlines practical and theoretical implications and offers concluding remarks.

2 Theoretical background and research questions

The proliferation of e-commerce in the web environment has had dramatic impacts on the business landscape in both the business-to-consumer and the business-to-business arenas. The internet has enabled an information explosion, characterised by rapidly changing technologies that facilitate improved communication channels and information media. This has necessitated the need for retailers to change the way they market their products and services to remain viable in an ever-increasing competitive global economy. Similarly, the internet has an impact on how consumers make their purchasing decisions because now they have access to a greater number of alternatives at little or no extra cost than in the traditional markets (Biswas, 2004). At the same time, this creates information overload that may be overwhelming and cause a huge cognitive burden on shoppers engaged in online product searches. Manual online comprehensive product price comparisons may take users many hours to complete. This has identified a need for the development and application of online search agents designed to assist consumers by forming more efficient and tailor-made consideration sets in the online shopping process, which can enhance the overall search efficiency of the consumer. Fortunately, online search agents or shopping bots can provide extensive product coverage within seconds (Kephart and Greenwald, 2002).

Theoretical conceptualisations of shopping bot technologies appeared soon after the first commercial websites were introduced as a solution for finding products. Their development was based on the assumption that price is the most important decision criteria for online shoppers (Machlis, 1997). In 1995, the first shopping bot (BargainFinder), which allowed consumers to compare music CD prices without visiting the actual vendors' websites, was officially introduced to the virtual marketplace. Today, online shopping bots can be categorised into two types, server-based and client-based solutions. Server-based shopping bots provide a centralised, usually free of charge, approach whereby price comparisons are performed on web servers. Users only need an internet connection to open a webpage that presents the bot. Examples include mySimon and BizRate. In contrast, client-based shopping bots require that a client software application be installed on individual users' personal computers. These types of bot providers often charge a fee for their services. These systems are customisable and can be deployed to perform 'watch-dog' type activities, such as scanning vendor sites and utilising different search engines to alert the consumer to predetermined price triggers (Chan et al., 2001). Copernic is the most popular client-based shopping bot.

A number of different revenue models for shopping bot applications exist and continue to evolve. Typically, bot vendors do not directly charge consumers for their services. Instead, they rely on selling advertising space and generate revenue streams from retailers who pay to be listed on their site. For example, depending on the arrangement, retailers may pay a flat subscription rate, a referral charge when a shopper is re-directed, or a purchase transaction fee. These business models have been the subject of much controversy over the last decade since there is a belief that shopping bots are biased towards those retailers that pay the most for preferential listings. In response, bot providers claim that even though they have financial arrangements with some retailers, they do not exclude others in their product comparisons.

There are a number of challenges that bot vendors have been facing since the birth of this technology. First, price often becomes a major criterion affecting user purchasing decisions. This is especially true with respect to commoditised products, or items that users may not physically open, try or review in brick-and-mortar stores. In some cases, a bot vendor may not possibly offer prices below those of its competitors, if, for example, the minimum prices are set by the product supplier. This, in turn, may result in lost customers and lower revenues. Second, despite a long history of shopping bots, many internet users are still unaware of this technology. Therefore, bot vendors have to invest heavily in advertising and promotion campaigns. Third, bot technologies are still immature and common industry standards are rare.

Despite a dramatic potential of shopping bots for e-commerce, only a handful of studies analysed this emerging technology. Three different approaches have been documented in the existing literature (Baye et al., 2003; Menczer et al., 2002; Mullikin and Grewal, 2006):

1 investigation of technical design that focuses on functionality, technical algorithms and software specifics

2 potential impact of bots on various economic issues including price dispersion, online market efficiency and information theory

3 consumer behaviours and reactions to the online marketplace, and the resulting marketing issues facing retailers.

Regrettably, there are very few documented attempts to study shopping bots. For example, a search on the 'shopping bot' keywords conducted on several major academic and practitioner databases revealed a lack of research: IEEE Explore – 2; the ACM Digital Library – 5; ProQuest – 54, 50 of which came from not peer-reviewed outlets; Google Scholar – 140 papers. Most of them only mentioned shopping bots rather than studying this technology. Nevertheless, several relevant studies have been done. Rowley (2000) empirically examined a number of shopping bots and concluded that there are dramatic differences in their search facilities and output results. Rowley (2002) argued that shopping bots affect online consumer behaviour, and Rao and Smith (2006) emphasised the importance of shopping bots for the online travel industry.

Sadeddin et al. (2007) performed a comprehensive empirical assessment of the functionality and performance of nine shopping bots. In their experiment, the researchers conducted searches for three different product categories, such as books, DVDs and CDs, and made several important conclusions that are of interest to online shoppers, bot developers, merchants and policy-makers. As a major direction for future research, the authors recommended a follow-up project to test the stability of their conclusions over time. The rationale was that the internet is a very dynamic space, shopping bot technologies have been continuously evolving, and new business approaches have frequently appeared. This in turn may affect the performance of bots. For example, Sadeddin et al. did not find any difference in book prices for the examined bots. At the same time, for DVDs and CDs, significant price differences existed. The researchers did not find the best bot with respect to its functionality and performance, and concluded that to identify the best price in the internet consumers should employ as many bots as possible. However, it is unknown whether these recommendations may be still applicable two years later[1] considering the accelerated pace of shopping bot technology changes.

Therefore, the purpose of this project is to replicate the study by Sadeddin et al. (2007). This investigation empirically evaluates the performance of shopping bots, focusing on consistency and accuracy of product search results, by performing a more comprehensive study utilising the same methodology and approach employed by Sadeddin et al. The present investigation not only builds on the learnings reported in this previous study, but also offers a comparison of results over time, testing the temporal stability of conclusions drawn earlier. It is expected to provide readers with useful insight into the reliability and performance of shopping bots. Shopping bot service providers, consumers, e-retailers and researchers may benefit from the findings reported in this paper. Consumers are given ideas on how to utilise shopping bots to maximise their returns. Similarly, useful insight can be made available to service providers that may facilitate improvements in bot performance and functionality in the future. Retailers would gain further insight into the strengths and weaknesses of shopping bots. This study may also add to the body of knowledge in this field, and establish additional baselines and foundations for further research.

Consistent with the previous project, the following four research questions are proposed:

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

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

Research Question 3: How accurate is the information and recommendations provided by shopping bots?

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

3 Methodology and results

3.1 Experiment description

The intention of this follow-up project was to test the temporal stability of previous results and conclusions two years later. For this, the same experimental approach was adopted, but a more comprehensive list of shopping bots was examined. Sixteen, rather than nine, shopping bots were randomly selected from an exhaustive list available at the website http://www.shoppingbots.info that offers the most complete and accurate list of bots. All comprehensive (i.e., bots that search for various types of products rather than concentrate on only one product) shopping bots were identified. Each name was written on a card, and 16 cards were blindly picked from the deck. Consistent with the original study, the intention was to focus on general (comprehensive) shopping bots with wide product coverage, therefore bots that specialised in particular product groupings were excluded from consideration. All of the selected bots were server-based solutions (see Table 1).

Table 1 List of comprehensive shopping bots utilised in the project

Name	*URL*
Become	www.become.com
BizRate	www.bizrate.com
BottomDollar	www.bottomdollar.com
Brilliant Shopper	www.brilliantshopper.com
Dealio	www.dealio.com
DealTime	www.dealtime.com
MSN Shopping	www.shopping.msn.com
MySimon	www.mysimon.com
PriceGrabber	www.pricegrabber.com
Pronto	www.pronto.com
Shop	www.shop.com
Shopping	www.shopping.com
Shopzilla	www.shopzilla.com
Smarter	www.smarter.com
SortPrice	www.sortprice.com
Yahoo Shopping	www.shopping.yahoo.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 or UPC number. The usage of ISBN or UPC codes allowed locating identical products that might be difficult to do by using title or keyword searches. Only new items were considered.

In conducting this experiment, a methodical process was established whereby each of the 16 shopping bots was used to comparison-shop online for each of the 80 products. Data were collected in 2008 according to the key criteria to quantify and compile shopping bot outputs for comparison. Table 2 outlines a summary of the process and criteria used in the compilation of data required to answer each research question.

Table 2 Data collection process

Research Question	*Procedures*
Price dispersion	For each of the 16 × 80 consideration sets returned by shopping bots, the lowest, highest and average price was recorded in data tables
Supplemental information	For each of the 16 shopping bots studied, observations were noted during use, and a summary table was generated
Accuracy and reliability	For each of the 16 × 80 consideration sets, each unique vendor site was visited to determine if the product was available for purchase. If the product was unavailable, this fact was recorded. If the product was available, it was determined whether it was listed at the bot-reported price. If not, a price discrepancy was accrued for that shopping bot, and price data for that vendor was excluded from the price dispersion statistics
Vendor coverage	The number of unique vendors returned by each of the 16 × 80 consideration sets was tabulated and used to calculated the average for each shopping bot

3.2 *Price dispersion assessment*

To answer the first research question, high, low and average product prices were compared by using ANOVA. It was concluded that the application of MANOVA was not possible because of variable interdependency (i.e., high and low prices are independent, but they influence average prices). Three sets of products:

1 books

2 DVDs

3 CDs were analysed independently.

The analysed data set included only items that were actually available on the vendor's website at the price reported by a shopping bot. Table 3 outlines the findings.

Table 3 Price dispersion analysis

	High price		*Low price*		*Average price*	
	F-value	*P-value*	*F-value*	*P-value*	*F-value*	*P-value*
Books ($n = 40$)	2.163(15;476)	<0.01	3.092(15;473)	<0.001	1.653(15;473)	ns
DVDs ($n = 20$)	2.690(15;237)	<0.001	1.907(15;239)	<0.05	0.564(15;237)	ns
CDs ($n = 20$)	1.499(15;269)	Ns	0.736(15;269)	ns	0.424(15;269)	ns

3.3 *Supplementary information assessment*

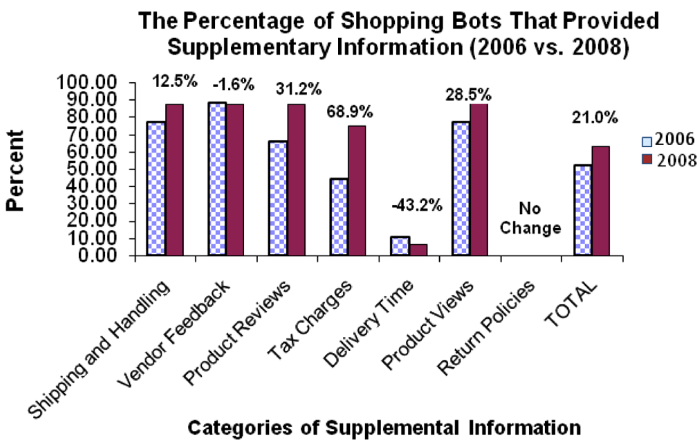
The objective of the second research question was to determine the comprehensiveness of supplementary product information provided by each shopping bot. Table 4 summarises the results. Note that to obtain shipping and handling fees, users had to enter their zip/postal code. MSN Shopping only indicated whether shipping and handling expenses were free of charge. Figure 1 outlines the changes in supplementary information over time. Overall, some improvement was observed.

Table 4 Supplementary information

	Shipping/ handling	*Vendor reviews*	*Product reviews*	*Taxes*	*Delivery time*	*Product views*	*Return policy*
Become	Yes	No	Yes	Yes	No	Yes	No
BizRate	Yes	Yes	Yes	Yes	No	Yes	No
BottomDollar	Yes	Yes	Yes	No	No	Yes	No
Brilliant Shopper	No	Yes	No	No	No	Yes	No
Dealio	Yes	Yes	No	Yes	No	Yes	No
DealTime	Yes	Yes	Yes	Yes	No	Yes	No
MSN Shopping	Yes*	Yes	Yes	No	No	Yes	No
mySimon	Yes	Yes	Yes	Yes	No	Yes	No
PriceGrabber	Yes	Yes	Yes	Yes	No	Yes	No
Pronto	Yes	Yes	Yes	Yes	No	Yes	No
Shop	Yes	Yes	Yes	Yes	Yes	Yes	No
Shopping	Yes	Yes	Yes	Yes	No	Yes	No
Shopzilla	Yes	Yes	Yes	Yes	No	Yes	No
Smarter	Yes	Yes	Yes	Yes	No	Yes	No
SortPrice	No	No	Yes	No	No	Yes	No
Yahoo Shopping	Yes	Yes	Yes	Yes	No	Yes	No

*Only specifies shipping/handling costs when free of charge.

Figure 1 Supplementary information comparison (see online version for colours)



3.4 *Information accuracy and online vendor coverage assessment*

The third research question pertained to the accuracy of results presented by shopping bots, and the fourth research question focused on e-merchant coverage. Each vendor's website was visited for each of the 80 × 16 consideration sets returned by shopping bots to collect the required information. Vendor information, such as name and website URL, was recorded. Five key measures, presented in Table 5, are provided to portray shopping bot accuracy and reliability. These are:

1 the number of times a price discrepancy was noted for each shopping bot

2 the number of times a product was not actually available for purchase (i.e., completely missing or sold out)

3 the average number of unique vendors

4 the ratio of the total wrong price cases to the average number of unique vendors

5 the ratio of the number of missing products to the average number of unique vendors.

The following non-parametric Spearman correlations were calculated: the total number of wrong price cases and the average number of unique vendors (0.86, $p < 0.001$), and the total number of missing products and the average number of unique vendors (0.37, ns). In the previous project by Sadeddin et al., the correlation between the total number of wrong price cases and the average number of unique vendors was 0.72, $p < 0.05$. It was also observed that the average number of unique vendors decreased from 6.32 in 2006 to only 3.82 in 2008.

Table 5 Information accuracy and online vendor coverage

Shopping Bot	*Total no. of wrong price cases*	*Total no. of missing products*	*Average no. of unique vendors*	*Ratio: no. of wrong price cases/no. of unique vendors*	*Ratio: no. of missing products/no. of unique vendors*
Become	30	30	1.85	16.22	16.22
BizRate	17	21	1.69	10.06	12.43
Bottomdollar	161	10	7.14	22.45	1.40
Brilliant Shopper	60	25	1.73	34.68	14.45
Dealio	20	22	1.63	12.27	13.50
DealTime	52	54	2.11	24.64	25.59
MSN Shopping	152	60	5.38	28.25	11.15
MySimon	147	131	2.64	55.68	49.62
PriceGrabber	166	84	7.23	22.96	11.62
Pronto	200	79	7.68	26.04	10.29
Shop	42	2	3.44	12.21	0.58
Shopping	68	22	2.01	33.83	10.95
Shopzilla	25	37	3.39	7.37	10.91
Smarter	71	5	4.14	17.15	1.21
SortPrice	25	15	1.55	16.13	9.68
Yahoo Shopping	160	54	7.43	21.53	7.27

4 Discussion and conclusion

4.1 Answers to research questions

The overall purpose of this project was to conduct a follow-up experiment to further empirically investigate the functionality and performance of online shopping bots. The intention was to build on and further test the temporal stability of the findings produced by Sadeddin et al. (2007). Consistent with the previous investigation, the same four research questions were revisited. Three categories of products were randomly selected: 40 books, 20 DVDs and 20 CDs. Online searches for each product were performed using 16 comprehensive (i.e., that search for a variety of products and do not concentrate on one product type only) shopping bots. On the basis of the findings, several interesting points emerged that deserve attention.

The goal of the *first research question* was to test price dispersion for similar product categories across different shopping bots. Table 6 presents the comparison of price results for 2006 vs. 2008. Overall, dramatic differences in bot performance were found; differences in price-based performance existed for almost half of all categories. In the previous study, no significant difference in price dispersion was observed for books. In contrast to the prior project, this subsequent study concludes that there are significant differences in low and high prices for books across different shopping bots. The higher degree of price dispersion suggests that consumers' use of numerous shopping bots is more likely to reveal good bargains online.

Similarly, in the case of DVDs, significant differences in shopping bot performance were found for high and low prices. These results agreed with those reported in the original study.

Table 6 Comparison of price results: 2006 vs. 2008

	High price		*Low price*		*Average price*	
	2006	*2008*	*2006*	*2008*	*2006*	*2008*
Books (*n = 40*)	No difference	Difference	No difference	Difference	No difference	No difference
DVDs (*n = 20*)	Difference	Difference	Difference	Difference	No difference	No difference
CDs (*n = 20*)	Difference	No difference	Difference	No difference	Difference	No difference

For CDs, no significant difference in low, high or average price was observed across the different shopping bots, contradictory to the prior study's findings, which noted significant differences in price dispersion. However, even with a lower degree of price dispersion measured across the different shopping bots, a visual inspection of the data set indicates that, for each CD, there was at least one price that was dramatically lower than those of the other bots. Specifically, the average difference of high and low prices for CDs reported across all 16 shopping bots is \$12.93, with the lowest being \$5.03 and the highest being \$24.21. Again, it is suggested that online shoppers may potentially find a real bargain for a specific product if they utilise numerous bots and compare the results. Inherently, this will necessitate higher levels of motivation and search effort required from shoppers. This method of online shopping, however, is still much better than the manual search techniques used on the internet search engines, such as Google, that requires visiting individual vendor websites.

For books and CDs, price dispersion results noted in this study contradict those from prior research. There are numerous plausible explanations. First, the electronic marketplace (e-marketplace) is in a continuous state of change; it tends to be volatile and somewhat unpredictable. More and more traditional brick-and-mortar companies continue to establish their presence in the online economy. As these markets mature, consumers and sellers alike vigorously vie to position themselves in the marketplace to attract more customers. For commoditised products, such as books, DVDs and CDs, price is perhaps the best way to differentiate from competition. Second, shopping bots, despite their potential and growing importance, are at an early stage of development. Shopping bots for e-commerce is a newly emerging technology that continues to evolve with advancements in the artificial intelligence field. Their level of complexity, sophistication and autonomy continues to progress, which inherently impacts their application and significance to buyers and sellers alike. Third, business relationships among e-merchants and bot providers are in a constant state of flux. Consider the end goal whereby each of the three stakeholders, e-merchants, shopping bot providers and consumers, are able to maximise their returns through the employment of online bots. That is, consumers are presented with completely accurate and unbiased recommendations, whereas e-merchants are able to differentiate themselves using online bot technology and maximise their margins, and shopping bot providers are able to maximise their revenue streams. Though no such ideal strategic or financial arrangements exist currently, business models that constantly evolve as new economic equilibriums are attained in the constant pursuit of this ideal condition.

It is concluded at this time, there is no 'best' or 'parsimonious' shopping bot in terms of price advantage. To find the best online deal, consumers should utilise and compare the recommendations of many different shopping bots. Though reducing consumer search efficiency, this has positive connotations with respect to stimulating healthy competition in the e-marketplace among shopping bot providers. Monopolisation or domination of the bot marketplace could potentially lead to undesirable conditions, not in the best interests of the consumer. Shopping bots must remain unbiased by maximising market coverage and the number of alternatives available for consumers. Overall, this conclusion is consistent with that of the initial project.

Recall that it was found that the average number of unique vendors decreased from 6.32 in 2006 to only 3.82 in 2008. It is possible that bot providers have reduced the number of vendors they deal with by eliminating those that offer incorrect results. Another explanation is that industry consolidation has occurred and some vendors merged together or went out of business.

The objective of the *second research question* was to review supplementary information presented by shopping bots. On the one hand, consistent with the original study, it is suggested that no shopping bot provides complete supplemental information of this nature, and in general, supplied information is only adequate. On the other hand, there has been a positive trend in functionality since more vendor- and product-specific information is currently provided. As evidenced in this study, there have been considerable advancements in shopping bot performance with respect to the amount of information provided, and if this trend continues, bots may be perfect in a few years. It is more likely that in future, most bots will present comprehensive supplementary product information that will assist users in their purchasing decisions and offer a very efficient method for online shopping.

The purpose of the *third and fourth research questions* was to investigate the accuracy of information and explore varying degrees of e-vendor coverage of different shopping bots. Two key measures were used to compare the level of accuracy of information returned by each shopping bot:

1 the number of price discrepancies returned by each shopping bot

2 the number of times a product was not actually available for purchase.

These totals were adjusted to the number of unique vendors for comparison with one another (ratios are shown in Table 5). Consistent with the findings in the original study, shopping bots varied in their degree of information truthfulness. First, the three most accurate shopping bots in terms of product availability were Shop, Smarter and BottomDollar, and the three least accurate ones were mySimon, DealTime and Become. These bots were determined most and least accurate based on the ratio of the number of times a product was unavailable for purchase to the average number of unique vendors returned by each shopping bot (lower values illustrate higher levels of accuracy, and higher values demonstrate lower levels of shopping bot accuracy). Second, the shopping bots yielding the least price discrepancies were Shopzilla, BizRate and Shop; those producing the most price differences were mySimon, Brilliant Shopper and MSN Shopping. The number of price discrepancies and the number of times a product was unavailable for purchase appears to be exclusive of one another. For example, BottomDollar is one of the three most accurate shopping bots according to the availability ratio, yet it is ranked sixth worst in terms of price accuracy.

With respect to e-vendor coverage, SortPrice and Pronto presented product information from the lowest and highest number of sellers, respectively. A major finding reported in the previous study was that the ratio of item unavailability to the average number of sellers remained consistent across the different shopping bots, demonstrating a positive relationship between the number of errors and the number of e-vendors. This subsequent study reiterates those findings for price discrepancies and, to a lesser degree, product availability. Recall that the following Spearman correlation values were obtained: the total number of wrong price cases and the average number of unique vendors (0.86, $p < 0.001$), and the total number of missing products and the average number of unique vendors (0.37, ns). If the number of examined bots was larger, the second correlation value would also become statistically significant. Therefore, the more vendors a shopping bot deals with, the higher the number of incorrect prices or unavailable products. At the same time, it was observed during the experiment that some online vendors were much more problematic than others in terms of information accuracy. It is more likely that bot providers would benefit from conducting a detailed vendor analysis and eliminating relationships with the most problematic ones.

4.2 Implications

The results of this study provide valuable insight into the usefulness of shopping bots as tools in the today's marketplace. The findings may offer some insights for buyers, sellers, shopping bot developers and researchers alike. They should prompt interest from each of these stakeholder groups. Results for each of the four components of this study are discussed here, along with their implications for the e-marketplace.

First, both the initial study and this project demonstrate that there is potential for consumers to realise excellent bargains through the use of online shopping bots. This opportunity exists owing to high levels of price dispersion, uncovered through the employment of shopping bots. Note that price dispersion results (compared across shopping bots) in this study were different from those in the preceding project for books and CDs. In the first study, there was no significant difference in price dispersion for books, whereas there were significant differences for high and low price. Similarly, in the first study, there were significant differences in price dispersion for CDs, and no significant differences in the second study. Remarkably, consistent in both studies, for product groups yielding insignificant price dispersion differences across shopping bots, excellent bargains were still available owing to individual product price range differences across shopping bots. Evidently, a high degree of price dispersion exists across e-vendors in the internet, even for homogeneous product categories, such as books, CDs and DVDs, lending to good deals. Internet users are encouraged to employ numerous shopping bots to locate the best deals, and levels of price dispersion would vary depending on product category as well as over time within the same product type. A suggested alternative is the concept of meta-shopping bots that would query numerous individual bots and present users with the best deals only.

Second, the findings of both studies concurred that the degree of supplementary information provided by shopping bots remains undersupplied, but continues to improve. There is a good deal of evidence supporting the fact that consumer buying behaviour can be shaped in part by such product information as shipping and handling costs, vendor reviews, product reviews, tax charges, delivery time, product views and return policies. In fact, price is an important but not the only criterion for decision making. Currently, almost no bots offer estimated delivery time and return policies. Therefore, a bot provider may differentiate itself from the competition by supplying end-users with extra information.

Third, consistent with the findings in the original study, shopping bots varied in their degree of information truthfulness; no bot generated perfectly accurate information in terms of product availability and price accuracy. It was observed that as the number of unique vendors increased, so did the number of incorrect prices, and, to some extent, missing products. It is somewhat intuitive to assume that as the number of alternatives increases so does the chance that inaccuracies will be encountered. On the one hand, to provide optimal value, shopping bots should offer price comparisons from as many e-vendors as possible, thereby providing users with more alternatives. On the other hand, it was observed during the experiment that some specific vendors tended to offer least accurate results. For example, by the end of this experiment, by looking at the results generated by each bot, the authors were able to predict which retailers would yield the least accurate information. It is recommended that retailers and bot providers work together to develop superior accurate and more comprehensive interfaces with up-to-date real-time information. Bot vendors may also want to periodically examine inaccurate information offered by e-vendors and eliminate unreliable ones from future searchers. Failing to do so can potentially limit economic performance for both retailers and bot providers alike. If a shopper frequently encounters false information from a particular shopping bot or vendor, he or she is more likely to develop poor perceptions of this bot and reduce its usage. It is more likely that accuracy, consistency, coverage, integrity and objectivity are the key factors that will determine the perceived usefulness and user acceptance of shopping bots.

4.3 Conclusions

This study tested temporal stability of the findings reported by Sadeddin et al. (2007) on the functionality and performance of shopping bots for e-commerce. During the project, a number of differences were discovered. As such, with the exception of price dispersion observations for books and CDs, the results were found to complement and confirm those obtained earlier. The most effective or efficient shopping bot does not yet exist; online shoppers are recommended to employ as many bots as possible to locate the lowest price. Bots demonstrated some improvement in the amount of supplementary information. There are still many inaccuracies with respect to the price correctness and actual product availability. Overall, the number of price discrepancies is strongly linked to the number of vendors, and the amount of missing products is somewhat related to how many vendors the bot deals with. It should be noted that the purpose of this project was very narrow in scope – to longitudinally test the findings of a previous study. It is for this reason the methodology and approach used in this follow-up project were the same as those of the initial investigation; otherwise, it would be difficult or even impossible to compare the results over time.

As electronic markets continue to evolve, shopping bots will inevitably play a pivotal role affecting how retailers position themselves and market their products. Similarly, consumers' abilities to locate the best deals through online search and comparison-shopping will heavily rely on the underpinnings of shopping bot technologies. While shopping bot developers and e-merchants continue to adapt to new ways of co-existence in the e-marketplace, consumers will have to recognise some of the inherent shortcomings of shopping bot usage, for example, biased results, potential inaccuracies and information deficiencies. At the same time, there is great potential for consumers to benefit through the use of these technologies. This study further extends our knowledge of performance and functionality of shopping bots at this point in time.

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Note

[1]Even though Sadeddin *et al.* published their study in 2007, data for this project were collected in 2006.