

What are the effects of different search engine interface designs on user behaviour?

Master thesis

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Management Summary

Studying user behaviour in the context of web search is becoming more and more popular. Search engines are the main way for internet users to conduct informational, navigational and transactional search tasks. The latter is of particular interest, as search engine result pages (SERPs) for transactional queries always include sponsored listings, i.e. ads. These sponsored listings are the main revenue stream for most search engine providers and each click on such a listing means the providers get paid a small sum, also called pay-per-click (PPC). Consequently, this means it is crucial for any search engine provider to design ads that draw the most amount of clicks and different providers use alternative SERP interface designs for transactional search queries.

This research focusses on whether there is a difference in transactional search behaviour between different search engine interface designs. Therefore, this study first reviewed scientific as well as non-scientific literature on this topic. Based on this review, we found that an experiment using an eye-tracking device is a very common method for research on user behaviour in online search. The review also revealed that visual hierarchy, competition for attention and banner blindness, are three important factors that may influence transactional search behaviour. This influence was studied by looking at Google and Bing's different interfaces using an eye-tracking device. In this experiment, participants were required to complete a number of transactional search tasks using both search engines.

The results show that only small differences were found in transactional search behaviour for two different search engine interfaces. Regarding the three factors, we found that the way visual hierarchy is organised is not directly related to transactional search behaviour. Moreover, competition for attention was not influential on search behaviour. Lastly, the banner blindness phenomenon only exists to a certain extent and search behaviour is only slightly influenced by this.

Overall, this study contributed to a deeper understanding of differences in search behaviour between different search engine interfaces. Although search engine interfaces for transactional queries differ, we see that they have little or no effect on user search behaviour.

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1. Introduction

The study of user behaviour in the context of web search can advance our understanding of fundamental behaviours involved in the online search process. It can also help design search engine interface designs, which can prove beneficial to both search engine providers and the people who use them. To date, a prominent method to delve deeper into user behaviour during web search is eye-tracking. A number of researchers have examined users' search behaviour in relation to navigational and informational queries (Joachims et al., 2007; Granka, Feusner, & Lorigo, 2008; Lorigo et al., 2008; Phillips, Yang, & Djasasbi, 2013). Their research suggests that the presentation of SERPs has a profound impact on users' viewing behaviour and selection of certain results. According to Höchstötter & Lewandowski (2009), the most crucial part for users and search engines is the stage when users are initially presented with the search engine results page (SERP) for their query. As a result, the first impression of a search engine page design is considered to be very important. However, an in-depth search on some popular search engines reveals that SERPs for informational and navigational queries seldom include more than two if any sponsored listings, and the page designs of different search engines are often strikingly similar. In contrast, search engine providers use different page designs for transactional queries, most notably image-based ads vs text-based ads. Furthermore, these queries include many sponsored listings at the top and to right of the SERP. This is important to consider, as major search engines predominantly use an advertising business model in which paid listings of the SERP generate the majority of their revenues (Brin & Page, 1998; Teece, 2010). As a result, paid listings dominate the initial SERP and only a few organic listings are visible. The majority of organic listings are only visible "below the fold", i.e. they can only be viewed when a user scrolls down.

The intent behind these queries is to make a transaction online and may include exact brand and product names (e.g. samsung galaxy s6) or be more general (e.g. shoes). They can also

include terms such as “buy”, “order”, or “purchase” which imply that the searcher is considering making an immediate purchase or a purchase in the near future. The layouts of these transactional SERPs is to have advertisements, i.e. pay-per-click (PPC) content, at the top of the page, and organic listings underneath. The reasoning behind this stems from the theory of visual hierarchy which suggests that listings at the top are likely to receive a great deal of attention (Faraday, 2000). In addition, larger objects, e.g. image-based ads which dominate the SERP, may receive more attention according to the competition for attention theory (Janiszewski, 1998). Nevertheless, many users circumnavigate the intrusive sponsored listings and instead view the organic listings (Chatterjee, 2008). This user behaviour is often linked to the banner blindness phenomenon, which states that users unintentionally or intentionally ignore and skip ads on a webpage (Drèze & Hussherr, 2003).

1.1 Research Problem and Question

Search engines such as Google, Bing, Yahoo etc. present their SERPs using different interface designs, in particular for transactional search queries. The most notable distinction is the integration of sponsored listings. Google uses image and text-based ads whereas other search engines solely use text-based ads. Further, more subtle, differences in search engine interface designs pertain to font type and size, and the placement of certain elements such as “related searches” (Höchstötter & Lewandowski, 2009). Consequently, the problem we face is whether user behaviour varies based on different designs of search engine interfaces.

In this study we want to explore users’ behaviour and break new ground by using eye-tracking. Guiding this study is the following research question:

Is there a difference in transactional search behaviour between different search engine interface designs?

In an experimental design we compare user behaviour between two search engine interfaces. In order to be able to answer the main research question the following sub-questions need to be answered.

To what extent does transactional search behaviour vary for different search engine interface designs in regards to the visual hierarchy theory?

To what extent does transactional search behaviour vary for different search engine interface designs in regards to the competition for attention theory?

To what extent does transactional search behaviour vary for different search engine interface designs in regards to the banner blindness phenomenon?

Which search results receive the majority of clicks from users?

To explore this, we apply eye-tracking technology which can detect where users look at a point in time, how long they look at something, and the path their eyes follow (Bergstrom & Schall, 2014). This technology helps us look deeper into user behaviour during online search and has been used to study human behaviour for decades (Lori Lorigo et al., 2008). While eye-tracking studies have explored general search behaviour on SERPs (Pan et al., 2004; Pan et al., 2007; Terai et al., 2008) only one scientific study by Lori Lorigo et al. (2008) has compared the viewing behaviour between two different search engines, however it focussed on navigational and informational search queries.

1.2 Aim and relevance of the study

The aim of this paper is to study differences in transactional search behaviour for the search engine page designs of Google and Bing, the two most popular search engines (comScore, 2015). This is a highly important topic for a number of reasons. Firstly, research of user behaviour in online search is becoming more and more popular in both the scientific and

business community. Secondly, understanding how users view SERP interfaces presented by different search engines is also of major interest. Does the viewing behaviour vary for different search engines interface designs? If so, why is this the case? Does this mean that one search engine interface design is more effective than the other and therefore superior? These are all interesting questions that still need to be answered, in order to fully understand user search behaviour of SERPs. Next, the scientific contribution and practical value behind this research are described.

The main scientific contribution of this research is to gain understanding of different search engine page designs and their effect on transactional search behaviour. Such an approach has previously not been conducted, yet is important considering the different page designs search engines use. The results of this study contribute to the existing literature of web search behaviour (Joachims, Granka, & Pan, 2005; Phillips et al., 2013; Poole & Ball, 2005 etc.). Additionally, this type of study is a way to get more research focussing on the different interface designs that search engines use and their effects on user behaviour. Furthermore, the eye-tracking method allowed a closer examination of three theories that are strongly related to web search behaviour. Overall, the scientific contribution of this thesis adds value to the current literature on user behaviour in regards to page interface designs, especially in relation to interfaces of a transactional nature.

The practical value of this study is understanding user behaviour which can help improve search engine usability and search engine marketing. Search engine developers can leverage the findings and optimise search engine interfaces for improved user experience. For businesses and online ad agencies, understanding the effects of different page designs on user behaviours can have large commercial implications in terms of which interfaces are more suitable for ad campaigns and more effective. Knowing how users view and perceive ads is

becoming increasingly important, as companies are spending more and more on online advertising (Statista, 2015).

The rest of this paper is organised as follows: Section 2 provides an overview and facts of both search engines and the differences and similarities of the SERPs. Furthermore, the existing body of knowledge on eye-tracking research on SERPs is also discussed. After that, we describe the theoretical model and pose our hypotheses. In the methods section, we detail the design of the experiment and also describe how the data analysis was carried out. Then, we present the results of the experiment in the following section and discuss the results as well as emphasise the practical and scientific implications. In the last section, we conclude about our work and provide the answer to the research question.

2. Literature review and overview of Google vs Bing

2.1 Google vs Bing

This first section provides a brief overview of the past and current trends regarding search engine market share. With this information we clearly argue why Google and Bing were chosen for the experiment. Next, the SERP interfaces are described to explicitly show the differences and similarities there are between the SERPs from the two search engines, as well as which areas of interest (AOIs) were considered for the experiment.

2.1.1 Google vs Bing: An overview of both search engines

Google the often heralded “king of search” has been the most popular search engine over the last decade. In this period, Google has won the so-called “search engine war” against AltaVista, Excite and most recently Yahoo. However, the introduction of Microsoft’s Bing in 2009, has seen a slow but growing shift in the search engine sphere. According to comScore (2015), Bing has amassed a 20.3% share in the US and become the second most popular

search engine (3rd: Yahoo, 12.7%) in only six years. Although Bing's high percentage in market share is not reflected in Europe, it only accounts for 2-3% of searches and Google <90% (Business Insider, 2014; Lunapark, 2014), its search market share is slowly increasing. As a result, more and more companies are advertising on Bing (Adobe Digital Index, 2014).

Overall, Bing's market share has mostly come at the expense of its search alliance partner Yahoo and the two search engines have traded places. Google still remains the most popular search engine, nevertheless, its search market share has fallen from 67.6% in May 2014 (comScore, 2014) to 64.2% in May 2015 (comScore, 2015). Furthermore, since Bing's launch in 2009 Google has frequently experimented with new elements (carousels, knowledge graphs etc.) on its SERPs, most notably its product listing ads. With these elements, Google has differentiated itself from Bing and other search engines in order to provide more targeted search results for users, better value for companies using Google AdWords and ultimately increase its search engine market share. In spite of that, Bing has slowly increased its search engine market share and a new search engine war has unfolded, clearly evident when Google accused Bing of copying search results (Search Engine Land, 2011).

2.1.2 Layout of SERPs

This section provides a short overview of results presentations in general web search engines and the main differences between Google and Bing. SERPs can be defined into different areas. The two main areas are the visible area and the scrolling area. The visible area, also known as "above the fold" or "above the scroll", is what users can see on a webpage without scrolling. All information, which is not immediately visible, is the scrolling area and is termed "below the fold" in web design.

Generally, SERPs of major search engines like Google, Yahoo!, and Bing consist of organic listings, paid listings and the search box (see Fig. 1). These are the most important and largest

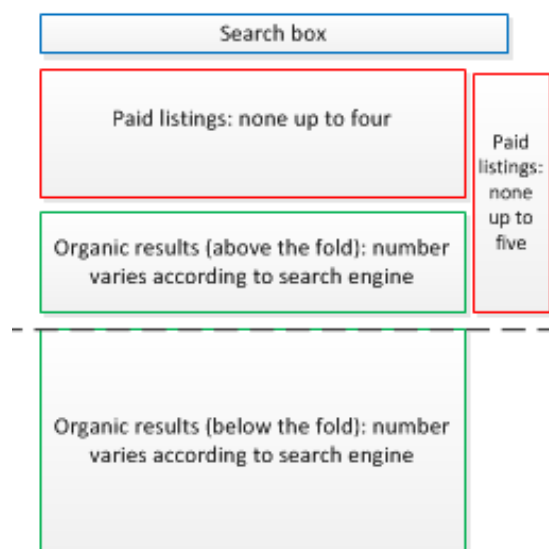


Figure 1 - Schematic representation of the 'general' SERP layout

areas of the every single SERP regardless of the search engine.

Organic SERP listings are natural listings generated by search engines based on their relevance to the search query. A number of factors such as search engine optimisation (SEO), which includes website content,

trustworthiness of the website, backlinking etc., are considered most important (Juon, Greiling & Buerkle, 2011). These organic listings can be

found at the central/ bottom of the visible area and cover the majority of the scroll area. In contrast, paid listings, or sponsored links are ads that businesses have paid for and can be found in the top/central and right area of SERPs. In order to have their ad appear in search engines as a sponsored link, businesses enter an auction and bid for a position according to certain parameters, most importantly relevance to a user's search query. This is called pay per click (PPC) advertising in which businesses pay the search engine for clicks on their ads. Lastly, the search box allows users to submit new queries, which sends the user to a new SERP once the search button has been clicked. These are the major elements of most search engines; however, search engines use different ways of integrating them. Therefore, differences and similarities between Google and Bing's SERPs, are discussed next. In addition, this section also covers the factors visual hierarchy, competition for attention and banner blindness and their relation to the different interfaces.

Figure 2 presents an example of a typical SERP for a transactional search query on Google. At the top of the SERP, the search box is lightly coloured and clearly visible next to the Google logo. Below, the paid listings at the top are situated in the focal area of the SERP. These listings include Google's product listing ads (PLAs), which are cost per click (CPC) ads online merchants purchase through AdWords. These ads distinguish themselves from regular text-based ads by using product images that include titles, prices and the URL. The header of these PLAs includes a link to Google shopping, which allows users to search and compare products from different vendors on Google's online shopping website. The top right text in the PLAs notifies users that the results are sponsored.



Figure 2: Example of a Google results screen as of June 2015, 1280x1024

The nature of the PLAs is an important aspect to consider and can be directly related to the three factors previously mentioned. In terms of both visual hierarchy and competition for attention, it can be assumed that the purpose of the PLAs is to manipulate users into paying attention to the top of the page and then viewing the page using a top-down approach. This would mean that the banner blindness factor would not occur. These assumptions behind Google's use of PLAs are supported by the following findings. According to Marin Software (2014), consumers prefer the richer and more engaging PLAs. Consequently, more people are inclined to look at the top part of the SERP, although ads are present. Furthermore, in 2013 the average click-through-rate (CTR) of PLAs increased by 6% while the CTR for text-based ads decreased by 13% (Marin Software, 2014).

Surrounding the PLAs below and to the right are traditional text-based ads with a page title, short snippet, URL and in some cases product ratings. Depending on the keyword, the number of text ads beneath the PLAs ranges from 1-2 and 1-5 to the right of the PLAs. These ads are highlighted with Google's yellow ad label and line barriers to distinguish them from the organic listings.

At the bottom third of the visible area the first organic listings appear. These listings appear due to their relevance to the search query. For transactional queries, the first listing is predominantly a link to the products official website, followed by further organic listings from online merchants and review sites. In some cases, new products with a lot of media attention may appear as 'in the news' listings immediately below the sponsored listings (e.g. Fig 2). In contrast to the visible area, the scroll area is dominated by organic listings that can

also include Google images of the products¹. Lastly, the bottom of the SERP includes searches related to the search query.

In comparison, Fig. 3 shows an example of a typical Bing results screen for a transactional query.

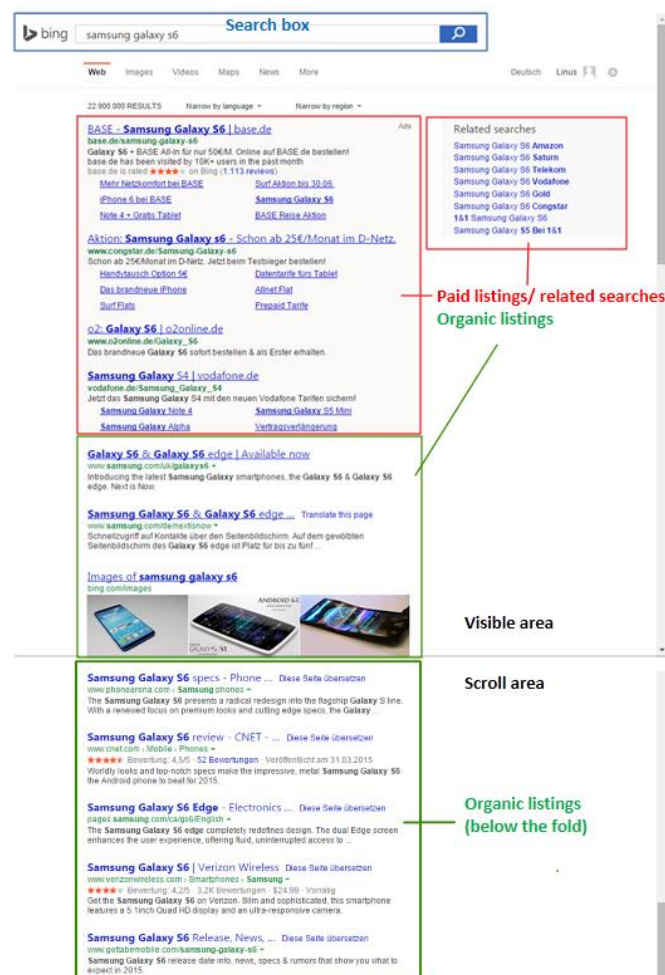


Figure 3 - Example of a Bing results screen as of June 2015, 1280x1024

The positions, layouts and designs (i.e. snippet and URL font and position) of organic listings and the search box are similar for both search engines. The only exceptions are that Bing uses a bold font for its search result page titles and in this example includes Bing images of

¹ In this example no further images were generated by the search engine. However, SERPs for other products show that Google often lists product images further down the SERP.

products at the bottom of the visible area instead of a news section. In terms of the search results, the products official website also ranks number one on Bing and a further result by CNET can also be found on Google's SERP. Aside from these similarities, the other search results are completely different.

As previously mentioned in section 1, the main differences between the search engines are the approaches in presenting SERPs for transactional queries. Instead of using PLAs, Bing uses traditional text-based paid listings at the top of its SERPs. These ads are more conservative compared to Google's and are nearly indistinguishable from the organic listings. The lightly coloured background, line barriers and small ad notification are what separate the two different kinds of listings. In terms of the design, Bing's paid listings include the page title, URL, snippets as well as additional sitelink extensions. These sitelinks allow companies to promote additional products and sections of their websites. However, the inclusion of sitelinks means that the listings are very large and only a few listings cover the majority of the visible area. Therefore, a maximum of four sponsored results are limited to this area. In terms of paid listings to the right, Bing uses similar type of ads as Google, but often not all of the four ad positions are used. The reason for this is believed to be the lack of competition on Bing Ads as many companies are still using Google AdWords (Wordstream, 2015). Consequently, the area to the right includes eight links to related searches, which appear below the ads when these are present. From the brief discussion, it can be seen that SERPs for transactional queries from two different search engines clearly present visual differences, especially differences regarding the paid listings.

Lastly, Bing's method for presenting sponsored listings is important to consider in relation to the factors concerning visual hierarchy, competition for attention and banner blindness. In terms of visual hierarchy, Bing's listings at the top of the page include snippets and sitelinks with more information than the organic listings, which may manipulate the visual hierarchy

of the SERP. This means, information at the top may be perceived to be of greater interest. However, the list-based format means that the competition for attention of listings is high (Hong, Thong, & Tam, 2005), therefore users do not necessarily look at listings at the top of the page. They might also look directly at the organic listings in the visible area. As a result, it can be assumed that banner blindness is more likely to occur either intentionally or unintentionally.

In summary, it can be said that the method used for presenting paid listings at the central/top area of the SERP varies between the two search engines. Other differences include the order and design of the listings, which are not as noticeable. In terms of similarities, the design and size of the organic listings are small similarities that can be found on both search engines. The major similarity is the layout of the SERPs. Both SERPs can be divided into the four key AOIs which are (1) sponsored/ paid listings at the top, (2) sponsored/ paid listings to the right, (3) organic listings above the fold, and (4) organic listings to the right. These four AOIs were also the main focus in the experiment and used for the subsequent analyses.

2.2 Eye-tracking research of SERPs

In this section, we give an overview of the most relevant eye-tracking papers analysing SERPs as well as search engine user types and viewing patterns. We will show that a number of studies have used eye-tracking to study search behaviour and viewing patterns on SERPs and webpages, which have provided interesting results. Reviewing the literature and describing the findings help put our study into the current context, and why it is relevant.

2.2.1 Introduction of eye-tracking studies of SERPs

Joachims, Granka, & Pan (2005) explored the way in which searchers examined a SERP. They found that a user's search behaviour is influenced by the position and relevance of the

results. Users have a strong bias towards results at higher positions on the SERP. Later studies by Bing Pan et al. (2007) and Guan & Cutrell (2007) reported similar findings. Their research found that users place their trust in the rank and relevancy of search results on Google's search engine and therefore users were more inclined to click on the first result entry.

Looking into how eye movements are influenced by the snippets of different search results, Cutrell & Guan (2007) reported that longer snippets improved search performance for informational tasks. In contrast, performance for navigational tasks degraded and transactional tasks were not included in the research.

More recent eye-tracking studies have also presented interesting results. Phillips et al. (2013) found that most users did not only view organic listings, but also viewed advertisements. What's more, results also showed that items at the top of the SERP received more attention than listings towards the bottom of the page. A study by Buscher & Dumais (2010) discovered that factors such as task type and ad quality influence how users view different components of SERPs. The visual attention users allocate towards organic results depends on both task type and ad quality. In addition, users' visual attention devoted to ads is contingent on ad quality, but not on task type.

2.2.2 Eye-tracking studies comparing multiple search engines

In the scientific community, most eye-tracking studies of SERPs use the Google search engine to conduct their research. In some cases, researchers have programmed their own SERP interfaces to resemble a commercial web search engine, e.g. Buscher & Dumais (2010). This approach allows researchers control of the SERP output, i.e. the number and position of search results. However, studies comparing viewing behaviours across search engines are scarce. Lorigo et al. (2008) examined the fixation counts, fixation duration and

time spent on tasks for Google and Yahoo. Their findings showed no differences in the user processing of the SERPs. In terms of non-scientific research, User Centric Inc. (now GfK, a market research company) twice examined users' distribution of attention on equivalent areas of Google and Bing. Their initial study (User Centric, 2009), which used informational and transactional tasks, found clear differences in the amount of attention attracted by the sponsored listings to the right. On Bing, 42% of participants looked at the sponsored links, while only 25% looked on Google. Other findings showed that Bing's "related searches" received greater attention than Google's. Two years later User Centric (2011) conducted the same research, but only allowed experienced users of both Google and Bing to participate in order to minimise variability among the sample. They found that users' visual attention was comparable. Most users focused on the sponsored listings at the top and the organic listings. The right pane attracted considerably less attention on both search engines. Differences emerged in the time participants spent looking at different areas, with Google's top sponsored and organic listings receiving more gaze time than Bing's.

2.2.3 Search engine user types and viewing patterns

Aula, Majaranta, & Rähkä (2005) found that two different types of searchers exist, i.e. exhaustive and economic searchers. Exhaustive searchers explore a SERP thoroughly and scroll up and down the SERP several times before choosing a search result to click on. In contrast, economic searchers sequentially examine a SERP from top to bottom and click on the most relevant search result. Klöckner, Wirschum, & Jameson (2004) reported similar findings and explored the order in which users explore a SERP before clicking on a result. Their research showed that most people use a linear pattern, evaluate each result in turn, and decide whether to click on a link before moving to the next result. Only 15% of users employed a more exhaustive search pattern in which all results were evaluated before clicking on a link. In addition to this research, several studies have focused on visualising

viewing behaviour by using heatmaps. Studies by Hotchkiss, Alston & Edwards (2006) and Nielsen (2006) revealed users follow an “F-shaped” pattern, i.e. the eyes scan the top of the page horizontally and then scan downwards. This pattern has also been termed the “Golden Triangle”, where the bottom of the triangle extends until the third or fourth search result. More recent research of Google’s SERPs found that the addition of various elements (e.g. knowledge graphs, product listings, carousels etc.) can cause a different search pattern (Mediative, 2014). Consequently, the highly coveted “Golden Triangle” no longer always exists. Furthermore, Mediative’s data (2014) showed that users are now scanning SERPs more vertically instead of horizontally. The reason for this is believed to be the increased adoption of mobile devices, which have habitually conditioned search engine users.

2.3 Key theories considered for eye-tracking analyses of SERPs

This section focusses on three theories related to web viewing behaviour and we justify why we chose these versus others found in the literature, before describing each in the following section.

As a general argument, we noticed that these three theories are the most recurring in the existing literature on web search behaviour. Countless studies, e.g. Djasasbi, Siegel, & Tullis (2011), Hervet & Gue (2011), Owens, Chaparro, & Palmer (2011), Djasasbi, Hall-Phillips, & Yang (2013), use these theories as their main focus of their research into web viewing behaviour. The specific reasons for choosing each theory are discussed next.

The argumentation for focussing on visual hierarchy stems from typical user behaviours. Research shows that the typical user behaviour in online search is to start viewing web pages on the top left handside (Lorigo et al., 2008). This is where search engine interfaces place their main search results, thus the theory of visual hierarchy is important on every single SERP. In terms of the competition for attention theory, we know that different sized items on

a webpage can alter typical user behaviours (Djamasbi, Hall-Phillips, et al., 2013). This needs to be considered as SERP interfaces include larger and smaller sized objects in different areas. Lastly, existing literature on the banner blindness phenomenon shows conflicting results. Some studies show that this phenomenon exists, whereas others refute this claim, which will be discussed in 2.3.3. As a result, this theory needs to be investigated further. This is the main line of reasoning for choosing these three theories. Given the experimental setting, we could not take more theories into account and limited them to these three which are all highly relevant. Other theories that were considered, but not deemed as important for the study purposes, were for example the “attractiveness bias theory” (Langlois et al., 2000) and “information foraging theory” (Pirolli & Fu, 2003).

Having explained the reasoning for choosing these well-known theories, the following subsections will describe each theory, review the main literature and explain why each is important in relation to this study.

2.3.1 Visual hierarchy

Expanding the idea of web viewing behaviour, Faraday (2000) defined visual hierarchy of a page as the order in which information is communicated to a user. He states that items placed at the top of a web page tend to be of greater importance. Consequently, Djamasbi, Siegel, & Tullis (2010) state that visual attention plays a crucial role in determining a person’s viewing behaviour. Furthermore, viewing a stimulus is a sequential cognitive activity, and users are only able to process one visual stimulus at a time. This is the case for stimuli that are adjacent to one another and therefore compete for a viewer’s attention (Desimone & Duncan, 1995), especially for items in close proximity to the focal area (Anstis, 1974). In addition, Web pages interact and exchange information with users through perceptual elements such as text, font size, colour, images or video. As well as a user’s own bias, visual hierarchy plays a

critical role in how users navigate a web page (Faraday, 2000). For example, the visual hierarchy of a page can be manipulated by changing the size of a focal object or making static elements dynamic. These changes can influence the viewing patterns and search process of users. Djamasbi, Siegel, & Tullis (2011) found that the complexity of visual hierarchy, i.e. larger items vs smaller ones and users' preferences to exhibit top down viewing, can affect the viewing pattern, and make users view webpages more carefully.

2.3.2 Competition for attention

The competition for attention theory states that each item on a web page competes for a user's attention (Janiszewski, 1998). For example, large objects that are not close to the focal area may compete for a user's attention and act as a distraction². Accordingly, Janiszewski (1998) posits that the amount of competition experienced by each item can be expressed numerically, by means of capturing the size and distance of competing objects. He states that the demand for attention of non-focal objects can be estimated by the ratio of the area it occupies and its distance from the focal vision. Hong, Thong, & Tam (2005) used this theory in the context of web pages. Their research shows that competition for attention is higher when items are arranged in a list format. Consequently, the format of a viewing area can play a significant role in a user's performance when searching for information. These results have profound implications for SERPs because search results on Bing are typically displayed in a list format. However, at the lower end of the initial SERP, Bing also includes images of products, people etc. that may distract from the focal area and compete for attention. In contrast, Google uses product images in the focal area to grab a user's attention, which can take away the attention from list search entries. This

² In this study, the focal area was defined as the area relating to the centre and most important part of the SERP, which is considered to be the sponsored listings at the top.

is particularly important as viewers have a tendency of viewing images before other items (Gregory, 2015).

2.3.3 *Banner blindness*

The term *banner blindness* refers to users unintentionally or intentionally ignoring and skipping ads on a webpage (Drèze & Hussherr, 2003). Banner blindness has also been described as users being ‘functionally blind’ to advertisements on web pages or SERPs (Benway & Lane, 1998; Burke, Hornof, Nilsen & Gorman, 2005). Research by Chatterjee (2008) shows that users tend to disregard adverts, especially those found in typical banner locations, and instead focus their attention on the web results or other web page elements. Despite the mixed reasons as to why users have a tendency to ‘act blind’ towards an advertisement, studies by Desimone & Duncan (1995), Pagendaum & Schaumburg (2006), Buscher & Dumais (2010), and Owens, Chaparro, & Palmer (2011) continue to reaffirm similar findings, i.e. web users tend to not view advertisements on a web page. This is especially frustrating for online marketers and advertisers who carefully craft their advertisements to solicit clicks from users as well as provide sponsored links related to the search query. Making it even more difficult for advertisers, a study by Owens et al. (2011) found that users exhibit ‘banner blindness’ to both text and image-based advertisements. According to Phillips et al. (2013), the type of search is also a factor, users ignore adverts unless perceived as useful in accomplishing their search task. In contrast to the findings suggesting that the banner blindness phenomenon exists, studies by Djamasbi, Hall-phillips, & Hall-phillips, (2013) and Phillips et al. (2013) found that users do look at advertisements on a webpage.

The three theories and the findings from existing literature are important to consider and help formulate the hypotheses in the next section, which will be tested with the help of the experiment.

2.4 Theoretical framework

Having studied the literature, we expect the three factors visual hierarchy, competition for attention and banner blindness to influence transactional search behaviour. This influence is studied by looking at Google and Bing's different interfaces. Next, we describe the theoretical framework (Fig. 4) and the hypotheses.

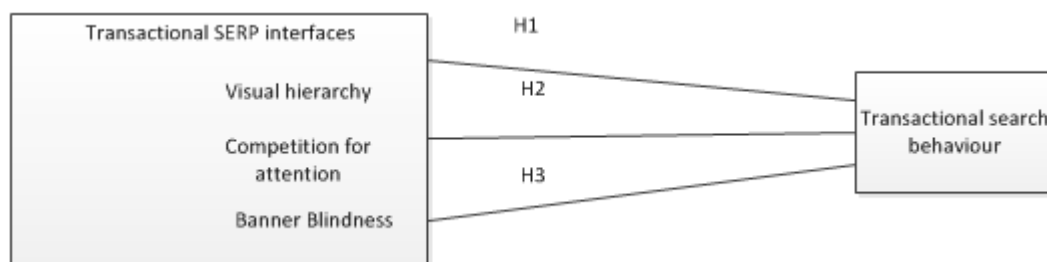


Figure 4 – Theoretical framework

The theory of visual hierarchy states that items placed at the top of a web page determine a person's search behaviour. The size of focal objects, text, images, font etc. can manipulate the visual hierarchy. With Google using its large and image-based PLAs and Bing using slightly shaded text-based ads the first hypothesis is:

H1: The way visual hierarchy is organised is directly related to transactional search behaviour.

In terms of competition for attention, Google's PLAs and product images dominate the visible area, whereas Bing's SERP is predominantly arranged as a text-based list format.

Furthermore, research shows that people have a tendency of viewing images before text.

Therefore, the following hypothesis is:

H2: Competition for attention has a direct relationship with transactional search behaviour.

Next, banner blindness is said to be a common phenomenon when people view webpages.

Nevertheless, a few studies show that people do look at advertisements. As a result, the following hypothesis is:

H3: Banner blindness has a direct relationship with transactional search behaviour.

These hypotheses will serve as a guide during the data analysis and help answer the research question of this study.

3. Methodology

3.1 Design

Most of the previous studies on web search behaviour analysis have focused on log files, click-through data and mouse tracking. Log files can provide valuable information about a user's web search behaviour in SERPs (Jansen, Jansen, Spink, & Spink, 2006; Mat-Hassan & Levene, 2005; Wedig & Madani, 2006). They reveal what users click but do not reveal what they are looking at. Click-through data and mouse tracking tools capture actions of the users but are very limited if the user is not moving the mouse and just browsing (Guo & Agichtein, 2010a, 2010b; Huang, White, & Dumais, 2011). In contrast, eye-tracking is a promising technique as the examination of eye movements has long been used in psychology and behavioural science research as a means of understanding a person's processes of reasoning and decision-making (Rayner, 2009). According to Just & Carpenter (1976), what a person is looking at indicates the thought "on top of the stack" of cognitive processes. This means that

recording eye movements can provide data of where a person's attention is being directed regarding a visual display. As a result, this study conducted an experiment of different search engines using eye-tracking.

The study utilised the Facelab 4.5 eye tracker and Gazetracker software to collect and analyse eye gaze data from users searching the web in a laboratory setting. Each subject participating in the study was required to carry out a number of search tasks using both Google and Bing. The SERPs were then analysed to reveal whether participants' viewing behaviour differed for the two search engines.

In this study, participant visual fixations were recorded during live web search. These were analysed in order to understand whether the viewing behaviour for transactional tasks differs when participants use two different search engines. Fixation was defined by Joachims et al. (2005) as, "a spatially stable gaze lasting for approximately 200-300 milliseconds, during which the visual attention is directed to a specific area of the visual display" (p. 156). Visual fixations indicate where a user is looking; however, areas of interest (AOIs) must be coded for each fixation in order to make the eye-tracking data useful.

The GazeTracker eye-tracking software allows researchers to draw AOIs, termed LookZones in GazeTracker, on specific sections of a stimulus, such as a SERP. Poole & Ball (2005) define an AOI as "an analysis method used in eye-tracking. Researchers define areas of interest over certain parts of a display or interface under evaluation, and analyse only the eye movements that fall within such areas" (p.10). AOIs are typically defined after the data has been collected, and this is done by manually drawing around those areas. The AOIs in this study were (1) sponsored results at the top left/centre, (2) sponsored results to the right, (3) the organic results above the fold and (4) organic results below the fold which represent the four largest and most important areas of a SERP (Höchstötter & Lewandowski, 2009). Once AOIs were defined, GazeTracker's analysis function automatically gathered data on the

fixations that landed within the boundaries of an AOI. Next, the tasks and queries used for this study are explained in detail..

Broadly speaking, all search tasks were of a transactional nature, which are based on the intent to perform some web-mediated activity such as a purchase, booking a flight, downloading of software, online banking etc. (Broder, 2002). In this study, this broad range of transactional tasks was narrowed down to transactional search queries with a strong commercial intent, i.e. when a user searches for a product or service, which is likely to be obtained on the internet (Lewandowski, Drechsler, & Von MacH, 2012). Due to the commercial nature, ads were a major component of the SERPs presented to the participants. The following reason also explains why navigational and informational queries were not chosen as search tasks for this experiment. Research shows that informational and navigational queries are the most prominent among users (Lewandowski et al., 2012), however, transactional queries are considered to be most relevant for search engines for a number of reasons. Firstly, these queries are most likely to deliver ROI in paid searches. If people are looking to make a transaction, i.e. looking to buy a specific product, a sponsored ad is more likely to deliver what users are searching for than results for informational or navigational tasks (Wordstream, 2012). Secondly, the sponsored listings (i.e. the main revenue streams for search engines) take up a lot of the “above the fold” space on SERPs for transactional queries. In contrast, informational and navigational search queries often have none or only a few sponsored listings at the top of the SERPs. Lastly, search engines embed their sponsored listings for transactional queries in different ways, which we have previously described.

Moving on to the experiment, every subject was required to conduct the same search tasks on both Bing and Google. All tasks involved using the actual real-time Google and Bing search engines and returned results were not altered in any way. Regarding the queries used for the

experiment, the literature does not specify what kind of search queries to use for eye-tracking studies on SERPs. Previous studies have all used different search queries. Consequently, this study used Google Trends to see which commercial queries were some of the most searched for in the Netherlands. Table 1 shows the four queries that participants had to enter during the experiment.

Table 1: *Search queries used by participants during the experiment*

Transactional task queries
samsung galaxy s6
ray ban aviator
converse all stars
canon camera

3.2 Data Collection

The subjects' eye movements were collected using Seeing Machines faceLAB 4.5 eye tracker that utilises two flea cameras mounted under the computer screen (LCD monitor, resolution 1280 by 1024 pixels). The eye-tracking device exploits the corneal and pupil reflections to determine the subject's eye position at a rate of 60Hz. From these two points, the faceLAB software computed pupil diameter and line of gaze for each eye fixation. This experiment utilised faceLAB's *precision gaze* configuration which allowed higher accuracy gaze tracking, i.e. fixations on very small objects (e.g. SERP snippets) were tracked by the device. Furthermore, the software also produces length of total time spent on the page and duration of fixations. Accompanying the faceLAB system, GazeTracker, a software application for eye-movement analysis, was used for acquiring a subject's eye movement data. The GazeTracker software runs separately from the faceLAB system and receives the data from the tracking

device. After the data is recorded, the GazeTracker software is able to analyse this data in different ways, e.g. GazeTrails, LookZones, Graphing etc.. All browsing history, including cookies, web page history, download history and passwords in Internet Explorer were deleted between subjects. This measure was taken so that a previous subject's browsing history did not influence the search results of later sessions. After all sessions were completed, the data were saved as OUT files and later processed.

3.3 Participants

Participants were undergraduate students from a Dutch university and were recruited through conversations and announcements on the university notice boards. Of the 20 appointments scheduled, 18 participants came to the university's lab and completed the study. Due to calibration issues four datasets had to be removed, therefore the final analyses included 14 datasets. Specifically, there were seven females and seven males, all between the ages of 20 and 24 ($\mu=21.86$). This convenience sampling method was chosen as it was easy to find students that met the criteria for participation. These criteria were:

- web experience (daily use of search engines as well as having previously used search engines for transactional search queries)
- familiarity with both Google and Bing's search engine, i.e. have used both search engines at least a number of times in the past
- no visual impairments, i.e. glasses or contact lenses

These were the important criteria for selecting subjects for the experiment. The criteria web experience and familiarity were chosen in order to reduce variability between the subjects, which was a major limitation in the UserCentric study in 2009, and one of the reasons a follow-up study was conducted in 2011. In addition, only students with no visual impairments were chosen. This was in accordance with the faceLab manual as eyewear, such

as glasses and contact lenses, can significantly distort the eye-tracking capability of the device.

In this study, the participants all reported that they used search engines for all kinds of tasks on a daily basis and considered themselves ‘experienced’ web users. Furthermore, most participants reported Google as their primary search engine; nevertheless all participants had also previously used Bing at some time or another. Lastly, no participants with visual impairments took part in the experiment.

3.4 Procedure

Each session was scheduled to last 30 minutes and participants were asked to conduct eight search tasks: four using Google and four using Bing. Approximately the first five minutes of each session were used to verify the participant’s identity and to have each student fill out a consent form and a short demographic questionnaire. Next, brief verbal instructions were provided and the participant was seated and his or her position was adjusted relative to the eye-tracking device. This was followed by the calibration, which used a nine-point standard calibration procedure for each participant. After calibration, faceLAB’s tracking quality indicator presented the accuracy of eye movements. For this study tracking quality was at least 75% (as recommended in the faceLAB manual). Participants with a tracking quality under the 75% threshold had to be recalibrated. After calibration, participants were permitted to ask questions before, during, and after a practise task, nevertheless, some participants asked questions during the experiment. The experiment started when the participants felt comfortable and the eye-tracking quality was consistently high. Participants were told to imagine themselves having or wanting to buy a new product, which would replace their current items. In this study, students were given specific task queries they should enter into the search engine. In order to avoid unnecessary head movements with printed instructions,

which can strongly affect the calibration, the task queries were read aloud. Each subject was told to view the SERPs and search as they typically would under normal conditions. The self-paced nature of this procedure helped eliminate sources of stress and allowed each participant to search at a natural pace. To end a web search for a query and view the next task, participants notified the researcher who would immediately give them the next query. In order to discourage rushing, participants were not notified of the maximum number of search tasks. Furthermore, to minimise order effects, the order of search queries and the order of the search engines were counterbalanced across the sample. After the final search of a session was performed, a discussion about the experiment took place. Participants were allowed to review their eye-movements with the use of GazeTracker's video function and describe their thoughts and decisions behind some of their viewing behaviours. For the subsequent analysis, only data sets which fulfilled the stringent calibration thresholds and task requirements were considered. In four cases, inaccurate and inconsistent results, e.g. invalid samples, were excluded and deleted from the data analysis. The following bulletin list summarises the procedure that was performed before, during and after the experiment for each participant.

- verbal instructions provided to participants
- seating position adjusted for camera configuration
- calibration (accuracy $\geq$ 75% threshold)
- (recalibration if accuracy $<$ 75% threshold)
- **start of experiment:**
 - task query read aloud
 - completion of task followed by new task query
- **end of experiment:** all tasks completed
- discussion + review of eye-recordings with participants
- review of datasets for invalid/ inconsistent samples

- exclusion of inconsistent datasets

This is a similar procedure as suggested by both the faceLAB and GazeTracker manuals. From a technical standpoint, a comprehensive step-by-step guide on how faceLAB and GazeTracker were used and integrated into the experiment can be found in Appendix A.

3.5 Analysis and Measures

A user's initial interaction with a webpage can have a significant impact on their behaviour (Djamasbi et al., 2011; Lindgaard, Fernandes, Dudek, & Brown, 2006). Thus, this study looked at a user's viewing behaviour from the time that a SERP was loaded to the time an action was taken by either clicking on a link or typing the query for the next search task. In order to measure this, fixations were used to measure users' attention. This is an important measurement because, while the field of vision of a user typically consists of numerous objects, one can only focus on one object at a given moment (Faraday, 2000). In addition, fixations have been declared as a reliable measure of attention and are regarded as an important indicator of viewing behaviour (Edward Cutrell & Guan, 2007; Djamasbi & Tullis, 2007). Lastly, previous studies by Lori Lorigo et al. (2008), Djamasbi & Hall-phillips (2013), and Phillips et al., (2013) have used metrics such as time on page, total fixation duration, number of fixations, fixation distribution and average fixation duration in their data analyses. Some of these metrics were also used in the data analysis of this experiment.

The following process was used to analyse the eye-tracking data utilising the GazeTracker software. First, GazeTracker collected the raw data as x, y, and z coordinates of gaze points on the computer screen. These points were inferred from changes in the distance between a participant's pupil and cornea. Spatially and temporally similar coordinates were combined into fixation points. The majority of these fixations lasted between 200-300ms as stated by Joachims et al. (2005). Next, the software calculated various metrics for each SERP and the

four AOIs previously defined in 4.1. These AOIs were manually configured for each SERP using GazeTracker's Lookzone (i.e. AOI) function, which allowed the experimenter to outline Lookzones using the mouse. After this, a dataset for each participant was exported as an OUT file from GazeTracker and opened in Microsoft's Notepad. Because there were 14 separate files and the data in these files was not arranged in a useful order and included numerous metrics, steps were taken to arrange the data in a workable way. Therefore, before the analysis began, a separate Excel analysis spreadsheet was created. In this spreadsheet the most relevant metrics, were transferred from the OUT file and subsequently used for the data analysis. In addition, the eye-movement recordings were also manually reviewed after the experiment. The last step, was to create aggregated heatmaps for each AOI. For this purpose, the data from the OUT files was cleansed and uploaded to "R", an open source statistical computing language and environment software, where it was coded and processed to create the heatmaps.

3.6 Reliability of methodology

This section addresses any reliability issues regarding the methodology. Both the faceLAB eye-tracking device/ software and the GazeTracker analysis tool were setup using the exact specifications provided by the respective manuals. These manuals clearly stated which settings and thresholds were important for this kind of experiment. The most important reliability issue was the eye-tracking accuracy. As previously mentioned, the faceLAB eye-tracker includes an eye-tracking quality gage, which shows a percentage of how accurate the device is. In cases where the accuracy dipped below the threshold the eye-tracker was re-calibrated. Moreover, reliability was also scrutinised with the help of the data in the OUT files in which "total tracking time lost" is listed as a metric. Datasets, in which more than three seconds of tracking time was lost, were not deemed reliable for the subsequent analysis. This brings us to the reliability of the analysis, which was based on similar analyses

performed by Pan et al. (2004) and Pan et al. (2007). Both studies used the GazeTracker software for collecting and analysing their data and this thesis used a similar approach with additional help from the manual. In terms of the metrics used for the analysis, we previously mentioned that time on page, total fixation duration, number of fixations are reliable metrics for this kind of eye-tracking study.

4. Results

As stated in H1, we expected that the way visual hierarchy is organised is directly related to transactional search behaviour. This was tested on the two different search engine interfaces, i.e. Google's PLAs and Bing's text-based ads. For this purpose we looked at the data for total time spent, number of fixations, duration of fixations in AOI#1, which comprised the paid listings at the top left/centre of the SERP.

In addition to the data obtained from the GazeTracker software, observations of search behaviour, were made both during and after the experiment, as well as aggregated heatmaps created for each AOI using R. Figures 5 and 6 show the areas that received the most amount of attention and how much time participants spent in each AOI for different search engine interfaces. Data from mean eye-tracking indices for sponsored listings at the top show that time spent by participants in this area was 5.41 secs on Google and 5.40 secs on Bing and therefore nearly identical (see Fig. 5 & 6).

We also found that the percentage of time spent in this zone in relation to the total time on the SERP only deviated by 1%. Moreover, we checked whether one of the search engine interfaces drew more/less fixations and longer/shorter fixation duration. Table 2 shows that the number of fixations and fixation duration were also very similar for both search engines.



Figure 5 - Aggregated percentage of viewers, mean time & heatmaps for AOIs on all Google SERPs (darker areas signify more fixations)

Consequently, the results do not support H1, meaning that the way visual hierarchy is organised is not directly related to transactional search behaviour. User behaviours were very similar, although the interfaces showed clear visual differences in this AOI. This is also supported by observations made during the experiment and showed that 100% of subjects began their searches by looking at AOI #1 and then followed a top-down approach on both search engines. A post-test review of the eye-movement recordings, which showed the gaze paths of participants, also validated these observations.

Table 2

Mean eye-tracking indices for sponsored listings at the top by search engine

Eye-tracking indices AOI#1 (sponsored listings at the top/left)	Bing	Google
Total time in AOI (seconds) (% of total time on page)	5.40 (18.4%)	5.41 (19.41%)
Number of fixations in zone (% of fixations per page)	7.76 (14.4%)	7.96 (16.08%)
Duration of fixations in zone (seconds)	0.244	0.243

These findings are also important for H3, where we hypothesized that banner blindness has a direct relationship with transactional search behaviour. This means that before scrolling to the organic listings, users would not look at the sponsored listings. From Table 2 we already know that users spent roughly 19% of the total time on the SERP looking at the sponsored listings at the top. Furthermore, data from the OUT files shows that 100% of the participants looked at the sponsored listings at the top for each search task (see Fig. 5 & 6). These findings clearly contradict the banner blindness phenomenon which is in line with the results presented by Djasmasbi et al. (2013) and Phillips et al. (2013). However, the sponsored listings to the right (i.e. AOI #2) also need to be considered. Overall, only 72.1% of participants looked at the sponsored listings to the right on Bing. The percentage was even lower on Google where only 58.9% of participants viewed sponsored listings to the right. This suggests that users have a tendency to ignore or overlook the sponsored listings to the right. The data from the OUT files also shows that when users did look at this area they spent very little time doing so (Google, 3.44secs; Bing, 2.98secs) and therefore the number of fixations was also low. Moreover, the fixation duration was also the lowest in this area for both search engines. On Google, the average fixation duration in this AOI was 239ms, which

was 9ms less than the average duration for the whole page. On Bing, the durations lasted 235ms, which was 14ms less than the average duration for the whole page. These small differences also show that this AOI was not as important to the participants than other AOIs where the duration of fixations was longer. Overall, we found that most of the data showed no support for H3. Before scrolling to the organic listings, 100% of users spent time viewing sponsored listings at the top/left of the SERP, therefore banner blindness did not occur. However, this was not always the case for sponsored listings to the right, which some users intentionally or unintentionally overlooked.



Figure 6 - Aggregated percentage of viewers, mean time & heatmaps for AOIs on all Bing SERPs (darker areas signify more fixations)

In H2, we hypothesized that competition for attention has a direct relationship with transactional search behaviour. Google's large PLAs would act as a distraction and grab more of users' attention than other items such as text-based listings. Data from Table 2 shows that the mean time spent in this area was 5.41 seconds and a mean fixation duration of 0.243ms. The easiest way to test H2 is to compare the aggregated heatmaps for the typical SERP interfaces of the two search engines. Figures 5 and 6 show that the images did not receive more fixations. Furthermore, user fixation duration and the time spent on Google's PLAs was not longer than in the equivalent area of Bing's interface. Table 2 shows near identical results, meaning although Google PLAs are image-based, users did not fixate longer on them than in comparison to Bing's text-based listings. Instead, the heatmaps for the first organic listings show a very competitive area of competition although being far less obvious than the images (see Fig. 5 & 6). To support this, Table 3 shows that the text-based listings in AOI #3, underneath the PLAs, received more attention, i.e. users spent 7.11 seconds in this area and fixation duration was 11ms longer. The heatmaps also show that other images, which dominated some aspects of certain AOIs (e.g. news headlines or product images), did not receive more attention. Figures 5 and 6 clearly show that the viewing behaviour of participants was scattered, i.e. they looked at many different listings. Therefore, the results do not support H2.

Table 3: *Mean eye-tracking indices for organic listings above the fold by search engine*

Eye-tracking indices AOI#3 (organic listings above the fold)	Bing	Google
Total time in AOI (seconds) (% of total time on page)	9.01 (30.8%)	7.11 (25.5%)
Number of fixations in zone (% of fixations per page)	13.80 (25.61%)	10.96 (22.14%)
Duration of fixations in zone (seconds)	0.249	0.254

In order to show just how similar transactional search behaviour was, Table 4 shows the mean eye-tracking indices for the whole time spent on the SERP. Participants spent a slightly longer time on Bing, the difference of which is similar to that found in the total time spent viewing the organic listings above the fold (see Table 3). Table 4 also shows that the number of fixations was only slightly higher on Google's SERP and the mean fixation durations are almost identical and only deviate by a fraction of 1ms.

Table 4: *Mean eye-tracking indices by search engine*

Eye-tracking indices	Bing	Google
Total time on page (seconds)	29.36	27.90
Number of fixations per page	53.88	49.5
Duration of fixations (seconds)	0.249	0.248

In addition to the eye-tracking data, observations of search and click behaviour were made both during and after the experiment. The observations during the experiment showed that users tend to scroll down and then return to the top of the page which support Hong et al.'s (2005) findings. These observations were also validated by reviewing the eye-movement recordings which showed the gaze paths of the participants. In terms of click behaviour, notes were taken on which result listings the participants clicked to complete the task. Figure 7 shows which link positions participants predominantly clicked on. With 23.21% on Bing and 21.43% on Google, the second position of the organic listings received the most amount of clicks. Overall, participants were more inclined to click on organic listings. Nevertheless, sponsored listings at the top did receive a large part of clicks, especially on Bing. As for sponsored listings to the right, these did not receive any of the clicks. The same can be said for organic listings at the very bottom of the SERP as well as the related searches.

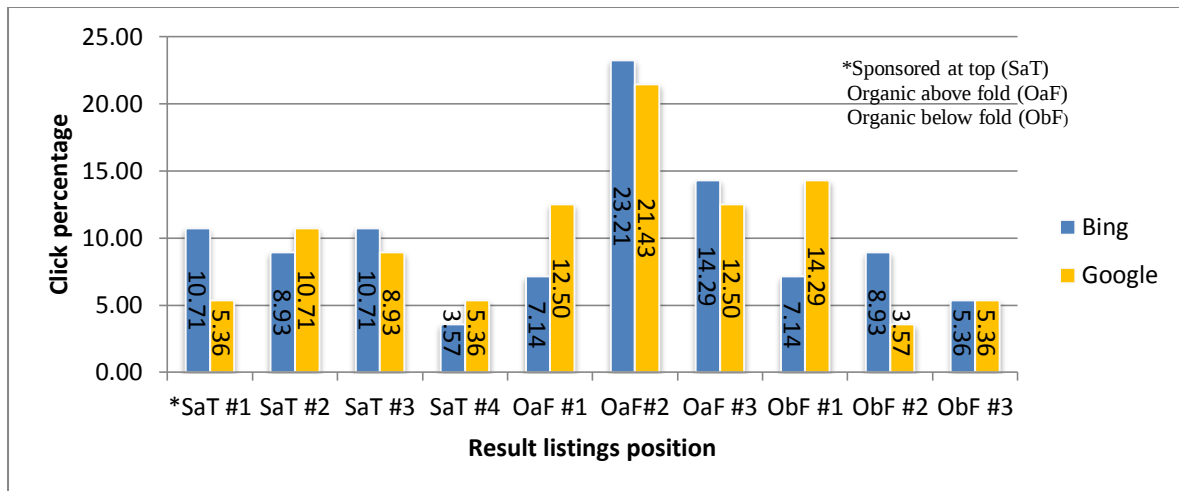


Figure 7: Click percentages of result listing positions

5. Discussion

This study sought to discover whether there were differences in transactional search between different search engine interface designs. The eye-tracking results collected and observations made during and after the experiment showed that only small differences were found in transactional search behaviour for the two typical page designs. Findings support that during the viewing of SERPs, most users looked at the first search results and followed a top-down approach. This means that the way visual hierarchy is organised does not matter as much in the case of transactional SERPs. The reason for this is that people have become used to the interfaces and the higher the placement of an entry, the more attention it receives (Faraday, 2000). In terms of banner blindness, this phenomenon only occurs to a slight degree regarding transactional SERPs. In the majority of cases, people spent time looking at sponsored listings because of the transactional nature of the task (UserCentric, 2009). This finding was also confirmed by participants after they had conducted the experiment. All of them said that they looked at the sponsored listings in order to not overlook a great offer or valuable information. However, whereas users spent time looking at the first entries to the left of the SERP, the same could not be said for sponsored listings to the right. The main explanation for this is that these listings are not in the focal area and users start viewing

SERPs at the top left corner. Additionally, the adoption of mobile devices has conditioned users to now scan more vertically and consequently ignore the majority of sponsored ads to the right or spend very little time viewing them. These findings are also similar to those found by research conducted by Mediative (2014).

In this study, it was also expected that the competition for attention has a direct relationship with transactional search behaviour. The images included in transactional SERP interfaces did not receive more attention. We assume that users viewed the sponsored listings with prejudgement. This means that no matter whether text-based links, images or videos are situated in the sponsored listings section, users only wanted to briefly scan this area before looking at the organic listings, which they deemed to be more relevant and more trustworthy (Mediative, 2014).

Concerning the click percentages, the findings show that users favour the second position of the organic listings on both search engines. Conversations with the participants after the experiment discovered why this was the case. Participants were reluctant to click on a sponsored listing, except when they felt they could not find what they were looking for. Again, prejudgement made them prefer organic over paid listings. As a result, users spent more time looking at organic listings and predominantly chose the second organic listing as it provided the most relevant content and was in the visible area. One might have expected that users would choose to click on the first organic listing, however, these listings were always links to the official websites of the products. Most participants were unwilling to click on these links as they felt they would not get the best deal on these sites.

Overall, the findings are clear, but no study is perfect. We followed an approach, i.e. methodology and analysis, similar to previous studies and this may be responsible for our results. An alternative methodology or question may have led to different outcomes.

5.1 Limitations

As with any lab experiment the generalizability of the results in this study are limited, in particular because of the sample size and tasks used. The participants were Generation Y users who are very experienced using Google, Bing and other search engines. This might have introduced bias into the results and a follow-up study with different generations should be considered. Secondly, there is no clear methodology on what kind of tasks to incorporate in eye-tracking experiments. The literature shows that every eye-tracking study uses different tasks and queries. Nevertheless, the same or similar tasks and queries can be used for an upcoming series of studies surrounding web viewing behaviour. With regard to eye-tracking as a method to investigate search behaviour, calibration issues and data analysis can be cumbersome and alternatives such as log-files or mouse tracking are less complex. As a result, the sample size is smaller than we had hoped for. Nevertheless, other studies have also used similar sample sizes (E Cutrell & Guan, 2007; Edward Cutrell & Guan, 2007; Lori Lorigo et al., 2008), but a larger sample is recommended. Lastly, all searches took place using real-time search engines. This means that since the experiment took place, the SERP interfaces for the same queries may appear differently today, as search engine providers regularly update their algorithms and include new elements.

5.2 Future research

Future studies can extend the findings of this study by using controlled search engines interfaces. Instead of using real-time search engines interfaces, researchers should programme their own interfaces that resemble commercial ones. This allows them to control certain stimuli. In addition, future studies can extend these results by examining different tasks or focus on different SERP areas that do not receive as much attention. Finally, the data

from this study can be combined with data on click through rates (CTRs) of listing positions, in order to measure whether a relationship between these two datasets exists.

5.3 Practical & scientific implications

In terms of the practical contribution, the results of this study are important for search engine developers. Knowing where people look can help developers identify which features are being overlooked and which ones are not. Consequently, these developers can optimise their search engine interfaces to improve a user's SERP experience. In addition, the data can help online advertisers and online companies determine which organic and sponsored SERP positions are most important when being ranked on search engines. Understanding how users view a SERP has large commercial implications. Online advertising agencies work with businesses in the area of search engine marketing. These agencies help clients develop online strategies for increasing traffic to their web site, e.g. placement and creation of sponsored listings or search engine optimisation (SEO). Better ad placements or ranking among the top organic listings can greatly improve traffic and therefore possible sales. According to Statista (2015), digital advertising spending is estimated to be 170 billion U.S. dollars in 2015. Moreover, forecasts show that this spending is estimated to increase year-on-year until 2018. These figures show that the digital advertising industry is booming and why it is such an important topic.

In terms of scientific implications, this study has investigated whether transactional search behaviour differs for varying search engine interfaces. This is important in order to understand if user behaviours are the same when they are interact with different interfaces. Previous scientific studies have only focussed on researching one search engine interface to investigate a user's web viewing behaviour. Furthermore, studies of transactional search tasks have also been neglected. As a result, this research addresses this clear gap and encourages

the scientific community to explore new approaches. Moreover, we have shown that key theories related to web behaviour are not always true and more research needs to be conducted in these areas.

6. Conclusion

Because the study of user behaviour in the context of web search is important for designing search engine interfaces, it is important to know which factors play a key role in the design process. For this purpose, we chose to investigate transactional search behaviour in regards to SERP interfaces of two search engines. Literature of the most important studies and theories was reviewed in order to design this research experiment. Overall, no major differences were found in the transactional search behaviour for two different search engine interface designs. Instead, we found a lot of similarities, although the approaches for presenting the SERPs varied. This leads us to the conclusion that fundamental search behaviours are responsible for how users view search engine interfaces that are of a transactional nature.

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Appendix

A) Step-by-step experimental procedure

The eye-tracking for this experiment was conducted using faceLAB 4.5 and GazeTracker. A step-by-step guide of how these tools were used in this experiment is described next. This will allow other researchers to replicate the study.

1. Start FaceLAB and choose pre-installed stereo-head. The stereo-head is responsible for the general camera configurations, i.e. angles, distance, precision etc.
2. This leads to the main window (Fig. 1) which displays information about the current head model, state of tracking and logging status. Under the *Display tab*, additional windows such as the video and control windows can be opened.

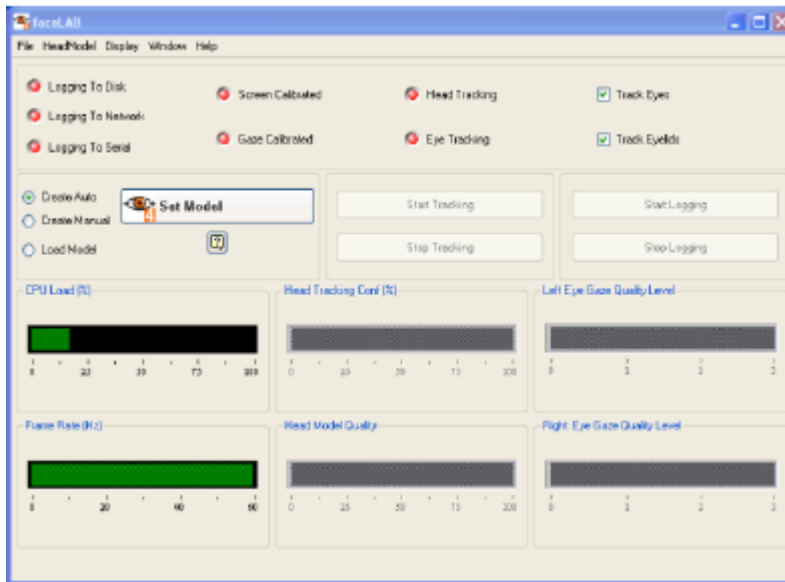


Figure 1 - faceLAB main window

3. Next, *Create Manual* needs to be clicked, followed by *Set Model*. This is performed for each participant, in order to configure models of their eyes and head with the eye-tracker.
4. The tracking option is set to *Front only*, and only tracks when participants have their faces fixated towards the screen. This option is the most precise, but participants are not allowed to turn their head otherwise no data is collected.
5. A snapshot of the head starts the model creation process (Fig. 2). The head positions of participants need to be adjusted so that the eyes are centred within the rectangle for both cameras A and B.

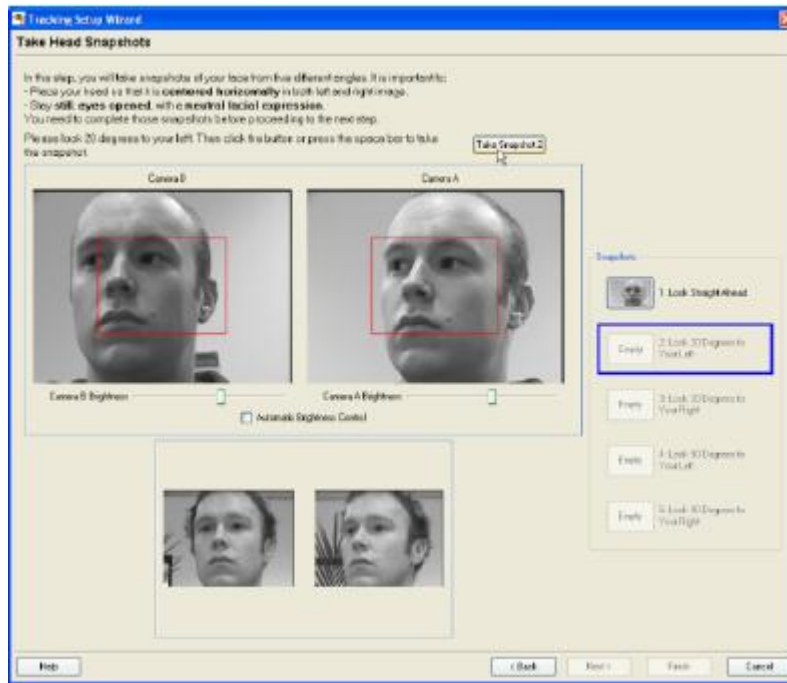


Figure 2- Adjustment of head position and snapshot tab

6. Next, the programme automatically marks the most relevant reference points with small red rectangles (Fig. 3). The most important reference points are the corners of the eyes and the mouth. Any misalignments need to be adjusted using the marker mode.

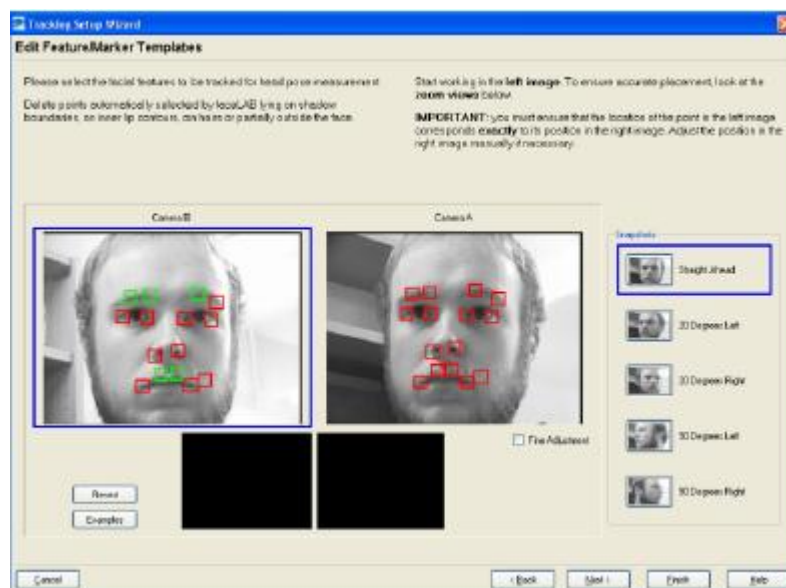


Figure 3- Markers for reference points

7. The *Adjust Head Tracking Parameters* window (Fig. 4) shows the tracking quality which should be at least 75%. Other eye-tracking parameters should not be changed. These steps finalise the camera configuration for a participants head-model and lead back to the *Display tab*.



Figure 4- Overview of head-tracking parameters

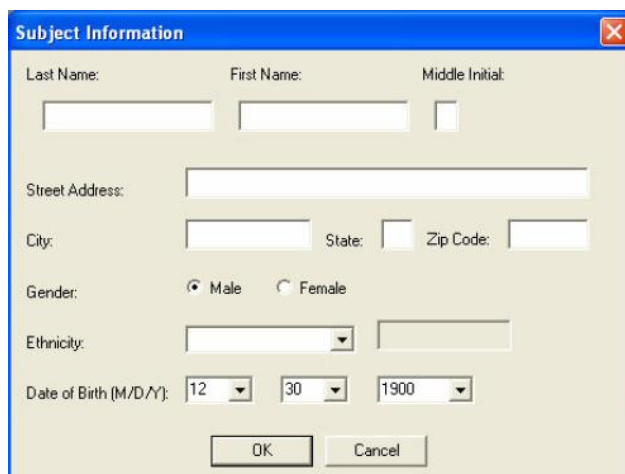
8. Under the *Window tab* a 9-point standard calibration procedure is used to verify that the calibration is accurate enough for the experiment.
9. The last step in faceLAB requires to click on the *Control window* and choose the *Log realtime* option. This connects faceLAB with GazeTracker. Once the *Start logging* and *Start tracking* options are clicked on the *Display tab*, faceLAB tracks a subject's eye movements.
10. In order to receive actual data, the GazeTracker data analysis software needs to be started and the *Software application* option needs to be chosen. This means that the software is configured to track data from web surfing.

11. Next, clicking on the red record button (Fig. 5) starts the experiment. Eye movements are logged by faceLAB and tracked in GazeTracker.



Figure 5- GazeTracker main tab

12. Subjects could start conducting the experiment and were instructed to complete the eight tasks that were read aloud to them. During the experiment, the faceLAB and GazeTracker windows were minimised and did not interfere.
13. Data was recorded and the experimenter was able to observe eye-movements and tracking quality on a separate monitor as well as take notes on which listings the subjects clicked.
14. Once the subjects were finished with the experiment, the *Stop* button on GazeTracker needs to be clicked to stop logging eye movement data.
15. Next, the data for a subject is saved under a 9 digit identification number and subject information (Fig. 6).



Subject Information

Last Name: First Name: Middle Initial:

Street Address:

City: State: Zip Code:

Gender: ☒ Male ☐ Female

Ethnicity:

Date of Birth (M/D/Y):

OK Cancel

Figure 6- GazeTracker subject information window

16. Now, the recorded data can be viewed in the *Recorded data dialog box* (Fig. 7).

Gazepoints, LookZones, GazeTrail and a video of the experiment can be viewed.

After the experiment, the subject and researcher viewed a video of the experiment, and the subject described some of his/her actions and choices. This last step concluded the experiment for a subject.

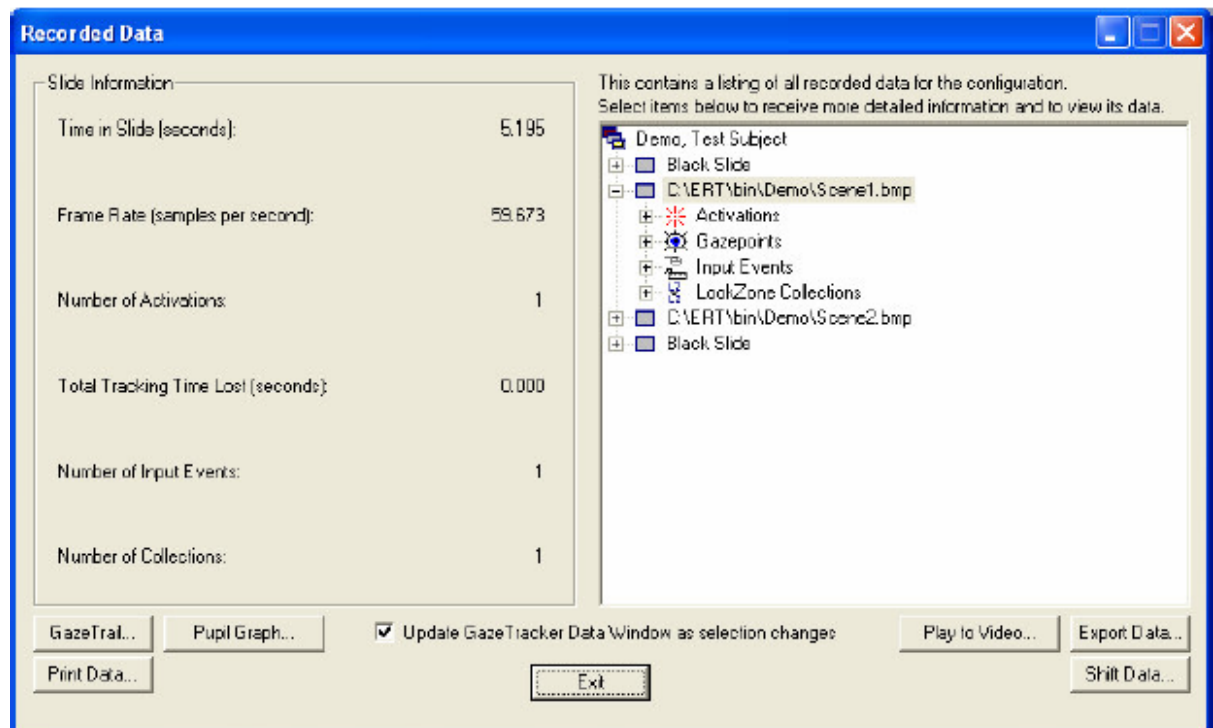


Figure 7- GT recorded data window

17. LookZones (i.e. AOIs) can be set for each SERP. This can be done by choosing the

LZ icon on the GT toolbar and LookZones can be manually drawn onto the SERP and

the LookZone properties can be saved (Fig. 8).

LookZone Properties

LookZone Name:

LookZone Description:

LookZone Owner:

Collection Owner

LookZones are grouped into collections. Collections allow you to easily organize your LookZones and to receive statistics on groups of zones.

☒ Select owning collection

☐ Create new collection

Collection name:

Figure 8- GT Lookzone properties

18. Lastly, the data of a subject is exported as an OUT file under the *Recorded data* dialog box (bottom right). This OUT file includes all the coordinates for the

[illegible]

In addition, overall metrics (Fig. 10) for each webpage can be viewed. This is the most important window and allows the researcher to conduct data analyses. GT offers data of the whole SERP, as well as data for each of the LookZones. The consensus of scientific studies is that data related to fixations are the most relevant for analyses. Figure 11 also shows an example of a screenshot of the eye-tracking recordings, which was used to infer further information after the experiment had been conducted.

19.

```

Overall metrics for slide http://www.bing.com/search?q=samsung+galaxy+s6
Time span shown in this file : All
Total time shown (seconds): 42.801
Total time tracked (seconds): 42.801
Total tracking time lost (seconds): 0.000
Total fixation duration (seconds): 15.580
Total time nonfixated excluding gaps (seconds): 27.221
Percent time tracked: 100.000
Percent tracking time lost: 0.000
Percent time fixated: 36.401
Percent time nonfixated excluding gaps: 63.599
Percent time fixated related to time tracked: 36.401
Percent time nonfixated related to time tracked: 63.599
Average pupil x diameter: 1.944
Average pupil y diameter: 1.050
Average pupil area: 1.635
Pupil x diameter std dev: 0.115
Pupil y diameter std dev: 0.821
Pupil area std dev: 1.298
Number of fixations: 70
Fixation count / Total time shown: 1.635
Fixation count / Total time tracked: 1.635
Average fixation duration (seconds): 0.223
Std dev fixation duration (seconds): 0.096
Average pupil x diameter in fixations: 1.960
Average pupil y diameter in fixations: 1.043
Average pupil area in fixations: 1.637
Pupil x diameter std dev in fixations: 0.104
Pupil y diameter std dev in fixations: 0.856
Pupil area std dev in fixations: 1.358
Number of gaze points: 2354
Gaze point count / Total time shown: 54.999
Gaze point count / Total time tracked: 54.999
Number of input events: 371
Fixation points in zones: 46
Percent fixations in zones: 65.714
Gaze points in zones: 1663
Percent gaze points in zones: 70.646
Input events in zones: 209
Percent input events in zones: 56.334

LookZone 1: LookZone #1
LookZone Description:
Sponsored Bing
Rectangle (pixels):
119,244
654,244
654,653
119,653
width (pixels):
535
Height (pixels):
409
Area (pixels squared):
218815
visibility (seconds):
Always visible
Duration actually shown (seconds):
42.801

Number of times zone observed: 12
Number of fixations before first arrival: 0
Duration before first fixation arrival (seconds): 6.922
Total time in zone (seconds): 7.814
Percentage of total fixations before first arrival: 0.000
Percentage of total slide time before first arrival: 0.512
Percent time spent in zone: 18.257
Average pupil x diameter: 1.913
Average pupil y diameter: 0.786
Average pupil area: 1.208

```

Figure 10- Screenshot of metrics obtained from GT

