Influence of Position Bias on Generational Consumer Behaviour

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Abstract

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Search engines play a pivotal role in guiding online consumer behaviour, yet the attention afforded to top-ranked search results can create a position bias that disproportionately influences which links users click. This thesis investigates how position bias in search engine rankings affects consumer choice, with a specific focus on generational differences. Building on literature in algorithmic bias, consumer psychology, and search engine optimisation, a mixed-method survey was designed incorporating both standard usage questions and controlled "mock SERP" scenarios. A total of 133 respondents across three age cohorts (16-34 years, 35-44 years, 45-69 years) completed an online questionnaire measuring click frequency, trust in top results, awareness of ranking factors, and open-ended perceptions of bias.

Quantitative analyses, including descriptive statistics and one-way ANOVAs, revealed that younger consumers (16-34 years) search more frequently, exhibit the highest awareness of SEO and ad labelling (M = 4.1 on a 5-point scale), and distribute clicks more evenly across the top three results. Middle-aged users (35-44 years) demonstrated the strongest position bias, with over 70% clicking the first result in both real-world and mock SERPs (M = 2.9 trust score). Older consumers (45-69 years) fell between these extremes, mixing position cues with brand familiarity when selecting links. Across all cohorts, brand recognition emerged as the single most powerful click driver (selected by 50-84% of respondents), often outweighing ranking position or snippet relevance. Qualitative responses confirmed that digital literacy and shopping experience moderate these effects.

This thesis has demonstrated that position bias in search engine rankings does not operate consistently but is filtered through generational perspectives of digital fluency and brand trust. These insights deepen our understanding of the connection between algorithmic design, marketing tactics, and user behaviour and awareness. Moving forward, search-engine developers should prioritise transparent ranking signals and ad disclosures, while marketers must balance SEO with visible credibility cues. Ultimately, equipping all generations with stronger digital-literacy tools will not only foster more informed online decision-making but also promote a fairer, more user-centred search ecosystem.

Key words
Position bias, search engines, consumer behaviour, generational differences, search engine optimisation (SEO)

Table of Contents

1 Introduction....1
1.1 Background....1
1.2 Objective....2
1.3 Research Question....2
1.4 Demarcation....3
1.5 Key concepts....4
2 Theoretical Framework....6
2.1 Search Engines....6
2.1.1 Search Engine Ranking....7
2.1.2 Google PageRank and Its Role in Position Bias....8
2.1.3 Search Engine Optimisation....9
2.2 Biases in Search Engines....10
2.2.1 Position Bias....11
2.2.2 Search Engine Manipulation Effect....12
2.3 Consumer Behaviour....13
2.3.1 Consumer Behaviour in Online Shopping....14
2.3.2 Consumer Behaviour Across Generations....15
2.3.3 Search Engine's Impact on Consumer Choices....16
3 Research Methodology....18
3.1 Research Design....18
3.2 Research Methods....19
3.3 Data Collection....20
3.4 Data Management and Analysis....21
4 Survey....22
4.1 Demographic Characteristics....22
4.2 General Search Behaviour and Trust in Rankings....23
4.3 Awareness and Perceptions of Search Engine Bias....27
4.4 Generational Differences in Search Behaviour....31
4.5 Interaction with Mock SERP Interactions....34
4.6 Summary of Key Findings....38
5 Conclusion....40
5.1 Discussion....40
5.2 Recommendations for Future Research....40
5.3 Reflection on the Thesis Process....41
Sources....42

Appendices 45
Appendix 1. Survey Questions 45

1 Introduction

This is a research-based bachelor's thesis for the Degree Programme in International Business in the major specialisation of marketing and sales at Haaga-Helia University of Applied Sciences. This research concerns search engine algorithms, consumer behaviour, and position ranking. The reader can expect to get a comprehensive overview of these topics throughout this thesis.

This chapter delves into the background and purpose of this thesis, outlining the objectives and research questions, and the scope of the project. As well as outlining the demarcation and limitations of the study. The chapter also clarifies the key concepts of this thesis for the reader for clarity.

1.1 Background

As browsing has become a daily, even hourly, activity for many, the use of search engines is becoming one of the most common activities done online. To keep up with the growing need for search engines and the web, companies and organisations must learn to take advantage of the power of search engines by producing high-quality content that responds to the consumer's wants and needs. (Heinze, Fletcher, Cruz & Fenton 2025)

Search engine optimisation has become one of the most fundamental parts of digital marketing in modern times. Rowles (2025, 78) states that search is a fundamental part of the user journey and that search engine optimisation is all about managing to appear at the top of search engine results with organic results. However, the problem of search engines and consumer behaviour lies in the fact that the vast majority of search engine users do not go beyond the first search engine results page. (Southern 2020) This would imply that if a digital presence, such as a web page, does not appear within the first search engine results page, and particularly the top half of that page, the likelihood it will be visited is substantially diminished. (Heinze et al. 2025, 229)

This insinuates that the positioning and ranking of the search engine results play a factor in consumer behaviour. Gao and Shah (2021, 1) mention that biased search results may affect user judgement, decision making, their beliefs and attitudes about information, and that the order in which search results are presented can create position bias. Position bias can be found everywhere – from a search engine results page to streaming services. Positioning impacts people constantly, with how much browsing has become a constant activity.

Recognising bias in search engines is important when trying to understand consumer behaviour and choices. Understanding biases and how to use the biases for marketers' advantage is important, since marketers will often exploit heuristics to convince consumers to make purchases.

(Psychology Today n.a.) Since positioning appears everywhere and is a constant presence in online platforms, marketers need to understand how to utilise positioning to their advantage.

1.2 Objective

The objective of this thesis is to examine how position bias in organic search engine rankings influences consumer behaviour, with a particular focus on generational differences between younger and older consumers. This research will analyse user behaviour during retail product searches by measuring how the placement of results affects selection, trust, and purchase decisions. By isolating position bias from other factors, such as broader online behaviours and other biases, this research provides a focused investigation into the impact of ranking positions on consumer behaviour.

By narrowing down the focus, the findings aim to offer actionable insights for marketers and search engine optimisation professionals to optimise strategies for different age groups, while also contributing to the broader discussion on algorithmic bias by highlighting how ranking positions shape consumer perceptions and choice. By raising awareness of position bias, this research also seeks to help consumers develop a more critical approach when interpreting search engine results.

1.3 Research Question

The central research problem this thesis aims to investigate is: **To what extent does position bias in search engine results influence consumer behaviour across different generations?**

The research question is driven by the increasing role of search engines in consumer behaviour and the assumption that users perceive top-ranking results as the most relevant. This research will provide insights into whether awareness of ranking bias differs by generation and how it affects user behaviour when selecting search results. The primary reason behind choosing this topic as the research problem was not only the author’s interest in search engine optimisation and consumer psychology, but also the growing reliance on search engines. Search engines are often seen as neutral ranking mechanisms, yet they are constantly influencing their users. By researching this problem, this thesis seeks to provide insights into how consumers interpret search rankings and how increased awareness could lead to more informed and critical engagement with search results.

There are further investigative questions that this thesis aims to seek answers for:

IQ1. How does search engine ranking influence consumers' selection of search results and purchasing decisions?

IQ2. How does position bias impact the level of trust in search engine results?

IQ3. What is the relationship between position bias and consumer purchase decisions or brand perceptions?

IQ4. How do different age groups perceive and engage with search result rankings when making online decisions?

Table 1. Overlay Matrix

Investigative questions	Theoretical Framework	Research Method	Survey Questions	Results
IQ1. How does search engine ranking influence consumers' selection of search results and purchasing decisions?	2.2	Theoretical framework & survey	5, 6, 10, 12, 13, 15, 16, 18, 19, 20, 21, 22, 25	4.2 and 4.5
IQ2. How does position bias impact the level of trust in search engine results?	2.3.3	Theoretical framework & survey	8, 9, 11, 15, 16, 20, 21, 23, 24, 22, 25	4.2 and 4.3
IQ3. What is the relationship between position bias and consumer purchase decisions or brand perceptions?	2.2.1	Theoretical framework & survey	7, 12, 13, 15, 16, 18, 19, 20, 21, 23, 24, 22, 25	4.2, 4.3, and 4.4
IQ4. How do different age groups perceive and engage to search result rankings when making online decisions?	2.3.2 and 2.3.3	Theoretical framework & survey	2, 14, 28	4.4 and 4.5

1.4 Demarcation

To ensure the scope of the research for this thesis remains both focused and manageable, several key limitations have been established. This thesis will exclusively examine the influence of position bias in organic search engine results on consumer behaviour within the retail shopping context, and a particular emphasis on comparing the behaviour of generational cohorts. This thesis is strictly limited to analysing how consumers interact with organic search results based solely on ranking position, thereby excluding broader aspects of search engine algorithms, digital advertising practices, or general online browsing behaviour.

This thesis will compare generational cohorts by focusing exclusively on the differences in search behaviour between younger and older consumers. This study is confined to the context of search behaviour related to retail shopping, which means it solely examines when consumers look for products online. So, this thesis will primarily examine organic search ranking, though consideration will be given to the impact of paid advertisements when needed – the core emphasis will remain on organic results.

To maintain a manageable scope, this study will exclude several aspects that potentially otherwise weaken the central objective. Specifically, the research will not consider the geographical location of users, nor will it provide a detailed analysis of paid advertising within search results or other forms of search engine biases. Instead, the focus will remain on consumers who frequently use major search engines, predominantly those who use Google, for retail shopping. This considered exclusion of region-specific search engines helps isolate the effect of position bias on consumer behaviour.

In terms of methodology, this study will rely on a structured online survey to collect data, with findings based on self-reported consumer behaviour and perceptions rather than direct observational tracking of search interactions. While this approach allows for broad participation, it may introduce some limitations related to self-perception bias in consumer responses. Furthermore, while the study aims to highlight practical insights for marketers and search engine optimisation professionals, it will not provide an extensive technical analysis of search engine ranking mechanisms.

By setting these boundaries, this thesis ensures a more focused and manageable scope that allows for a detailed examination of how position bias impacts consumer choices across generations. This ensures the study will be a targeted and in-depth examination of the topic.

1.5 Key concepts

Search engines are software tools that help users locate information on the internet. Search engines can provide the search results quickly by scanning the Internet continuously and indexing every page they find. (Pickle 2022)

A search engine results page (SERP) is the list of results that the search engine has calculated when a user of a search engine types in a query. It is the complete HTML page output given in response to a search query entered by a user when using a search engine. (Heinze et al. 2025, 236; Lewandowski, D. & Kammerer, Y. 2021, 1485-1486)

Search engine optimisation (SEO) is the process of making a page rank as highly as possible on a search engine when someone types in a query. The higher the page ranks in the results page, the more traffic it is likely to generate. (Baker 2022)

Algorithms are sets of instructions that guide a computer in following specific steps to achieve a particular objective. Search engine algorithms are a collection of formulas that determine the quality and relevance of a web page to the user’s query. (Cox 2022)

Position bias in search engine ranking is when the consumer is more likely to engage with something based on where the item is shown. Typically, the top-ranked items are more engaging. The top items that receive more clicks based only on their position within the search results is what position bias is. (Yates 2024; Grebennikov 2023)

2 Theoretical Framework

This thesis intends to analyse the current situation of search engines and how the ranking of search results occurs. Following this, the thesis will let the reader understand what key concepts regarding biases in search engines are, such as position bias and search engine manipulation effect. Finally, the relationship between search engines, biases, and consumer behaviour will be discussed.

2.1 Search Engines

When users seek content, information, or tools on devices such as smartphones, tablets, or laptops, they rely on search engines to deliver a ranked list of links. The SERP is designed to present the most relevant webpages for their queries. (Maillé, Maudet, Simon & Tuffin 2022, 3) Despite users becoming more adept at forming queries on search engines, they are becoming increasingly more dependent on search engines to provide accurate answers quickly. (Heinze et al. 2025, 236) Their reliance on search engines is critical in understanding how the ordering of results may introduce position bias, ultimately influencing consumer behaviour.

The global search market is dominated by several major players, which include Google, Yahoo, Baidu, and Yandex. However, Google remains by far the number one search engine used across the world, holding a market share of 78.83% in desktop searches and 93.82% in mobile searches as of January 2025. (Statcounter 2025a; Statcounter 2025b) This makes Google undoubtedly the most used search engine globally and makes it one of the most influential platforms globally. Given Google's prominence, its ranking mechanisms are central to discussions on position bias. The way these engines rank content directly affects which pages consumers are likely to see and engage with.

Search engines employ various algorithms to generate SERPs, these algorithms primarily fall into four categories: crawler-based search engines, human-powered directories, hybrid search engines, and meta search engines. (Geeks for Geeks 2024) Crawler-based engines use spiders to continuously crawl the web, index pages, and then retrieve results based on the query. Human-powered directories rely on manual categorisation of websites, while hybrid engines, such as those used by Google and Yahoo, combine automated crawling with human curation to improve overall result quality. Meta search engines combine results from multiple sources. (Geeks for Geeks 2024) Even though all these mechanisms differ, they all have the same aim, which is to deliver relevant content, and their inherent ranking processes are the basis for position bias, where higher-ranked results tend to garner more user attention regardless of fundamental content quality.

Search engines are constantly going through data and results to deliver instant and relevant responses to the user's queries. With how often people use search engines to seek information for the most mundane queries, these search engines have to continuously evolve to match the need for information and different forms of information. Understanding the operational details of search engines is important to examine how the position of a result in the SERP can influence consumer selection and trust.

2.1.1 Search Engine Ranking

Search engines utilise computationally demanding algorithms to generate ranked lists of results on SERPs and the rankings of them. For instance, Google's PageRank is an example of an algorithm created to assess a webpage's relevance and authority by analysing the number and quality of incoming links. (Maillé et al. 2022, 8) However, rankings are not determined solely by these internal factors, like the computational algorithms. Eternal factors, such as search engine optimisation strategies, also play a crucial role in enhancing a webpage's position and ranking. (Lewandowski & Schulteiß 2023, 1028) This connection between internal and external factors highlights how search engine ranking is shaped by both technological and strategic optimisation techniques.

As users tend to engage overwhelmingly with the top results on a results page, these ranking methods have a heavy impact on consumer behaviour. These algorithms factor in user satisfaction metrics, thereby prioritising results that are most likely to meet a user's intent and needs, as well as engagement metrics. (Lewandowski & Schulteiß 2023, 1027) In addition to these internal algorithmic elements, strategic practices such as SEO also play a role in shaping visibility, further influencing which results rise to the top. As Heinze et al. (2025) explain, SEO strategies are deliberately designed to match the expectations of ranking systems by boosting pages' positions by aligning with known ranking factors. These algorithms are designed to enhance the user experience and will rank webpages higher based on the engagement users show webpages. When users and consumers engage primarily with the top results, these algorithms will focus prioritisation of these results rather than giving attention to those further down the list. As a result, search engines function as gatekeepers of information, steering consumer choices toward the most visible options.

Despite the role of user experience in ranking algorithms, many users remain unaware of how search rankings shape their decisions. There is a common misconception that organic rankings are purely objective when, in reality, they are influenced by various factors that introduce ranking and positioning bias. These factors can include SEO, paying search engines directly to prioritise their webpages, and various other methods. One of the most recent studies done on search engine ranking by Lewandowski and Schulteiß (2023, 1033) found that a majority of users do not believe that directly paying Google can improve organic rankings and result in a higher position in the search results. This highlights a gap in users' understanding of how search engine ranking works. This lack of knowledge raises concerns about how search engines manipulate consumer choices, as users may not fully realise the complexities behind the search results they see.

When users tend to trust and engage with top-ranked results only, they are unknowingly limiting their options by selecting from a narrow set of highly visible choices. Consumers will often perceive higher ranked results as more relevant or superior in quality, even though these rankings are influenced by both internal and external factors rather than purely an objective measure of quality. (Epstein, Robertson, Lazer & Wilson 2017, 3) This significantly affects consumer choices, as products, services, and brands that appear at the top of search results manage to gain a competitive advantage simply due to their visibility. Ultimately, the way search engines rank content influences consumer behaviour by shaping their awareness, preferences, and purchase intent.

2.1.2 Google PageRank and Its Role in Position Bias

Historically, one of the earliest and most influential ranking systems used for search engines is PageRank. Page and Brin (1998) developed PageRank and Google to keep up with the dramatic growth of the web and produce search engine technology that would manage to grow alongside the web. When designing Google, they took into consideration the growth rate that the Web was showing in the late 90s. Google and PageRank were designed to manage and scale extremely large data sets well. The main goal of Google, as a search engine, was to improve the quality of web search in the late 90s and effectively manage to growth of the web. (Page & Brin 1998)

PageRank measures the importance of web pages based on link structures, assigning a ranking score to pages based on the number and quality of incoming links, which operates under the assumption that the more cited pages are more relevant. (Page & Brin 1998) It is considered an objective measure of the web page’s importance, which aligns with how people perceive importance. Designed to be a model of user behaviour, PageRank replicates how people rank web pages through a more effective and scalable way. In technical terms, PageRank represents the probability that a random surfer visits a page, with higher-ranked pages being more likely to attract clicks. (Page & Brin 1998) This ranking system also reinforces ranking bias that is prevalent in search engines, as users will disproportionately trust and engage with the top-ranked results only, often overlooking lower-ranked pages regardless of their actual relevance or quality.

Although Google’s ranking systems have evolved and the original PageRank has been retired, it continues to remain an important algorithm in search engines, and it plays a key role in the current algorithms. It was created to identify valuable content and reward sites that have high-quality backlinks, discourage link manipulation, and organise web content by relevance and authority.

(Varangouli 2025) However, not all votes are equal in PageRank – a link from a page with a higher authority is stronger than a link from a lower-authority page. Pages that link to many different sites weaken the authority of the link. (Varangouli 2025)

Leaked internal Google documents from 2024 have shown that multiple versions of PageRank are still in use within Google's search engine and remain a core component of their ranking systems today. (Varangouli 2025) This would mean that PageRank is at the core of search engines used currently; the same basis of the algorithm for ranking pages based on their worthiness is at the root of each search engine. Google regularly improves and modifies its ranking systems to manage the constant stream of links and queries, this is done through rigorous testing and evaluation. (Google 2024) The same principle from the original PageRank persists: higher ranked pages will receive significantly more visibility and engagement, which reinforces a form of position bias – users tend to trust and click on the top ranked results disproportionately.

Companies and organisations want their web page's rank to be high – they want to rank at the top of their target keywords. Regarding Google's top search results, the first organic search result will have an average CTR of 27.6%, while a result in tenth position is ten times less likely to be clicked. (Dean 2025) Additionally, Dean (2025) claims that only 0.63% of users will navigate to the second page of results, which emphasises the disproportionate attention that is given to the first few rankings. This supports the need for companies to optimise their strategies, as securing a top position can drastically impact visibility and engagement.

By favouring established, well-linked pages, PageRank inherently contributes to position bias, as users are more likely to interact with the highest-ranked results. This makes ranking placement a critical determinant of user behaviour and how a user will choose which web pages they will engage with.

2.1.3 Search Engine Optimisation

The core objective of search engine optimisation (SEO) is to improve a webpage's ranking in organic search results to secure a prominent position on the SERP. (Heinze et al. 2025, 251) Given that most users tend to click top-ranked results due to position bias, securing a high-ranking position is crucial for visibility and engagement. Organisations will aim to rank high in the results for their name and any relevant brands. (Heinze et al. 2025, 251)

Organisations will focus on optimising their web pages based on key elements such as page titles, headings, copy, link text, file names, and alt text, all of which signal relevance to the algorithms. (Rowles 2025, 81-89) These are the key areas that organisations will take into consideration for search engines to rank and weigh the relevance based on these areas.

The ranking of search results is determined by complex algorithms that analyse various factors, including content relevance, user behaviour, and external signals such as backlinks. (Heinze et al. 2025, 236) Search engine spiders or crawlers continuously scan websites, follow links, and index content to determine the ranking potential. (Rowles 2025, 81-89) Techniques such as on-page optimisation and link building are central to SEO, as they help demonstrate the authority and merit of a webpage, thereby influencing its position in the SERP. On-page optimisation, which is all about the careful placement of correct words in the correct places, and link building, which is about gaining endorsements from outside sources on the authority and merit of the content. These two factors play a key role in signalling relevance to search engines. (Rowles 2025, 88-93)

In addition to optimising content for better ranking, SEO also aims to deliver a positive user experience. For example, Google will favour websites with fast page speeds, responsiveness, and stability, ensuring users can navigate content smoothly. (Rowles 2025, 83) This is significant because if users frequently click on a result but quickly return to the SERP, search engines interpret this as a signal that the page did not meet expectations, which may subsequently lower its ranking over time. (Rowles 2025, 94)

While organic search remains a cornerstone of digital marketing, SEO exists alongside pay-per-click (PPC) advertising. PPC advertising offers an alternative way to gain visibility and is the other side of search. (Rowles 2025, 97) Unlike SEO, which is a long-term strategy aimed at achieving sustained top rankings, PPC enables businesses to gain immediate visibility through paid placements. However, even paid placements are subject to evaluation-based relevance and quality. The cost per click can become particularly expensive, notably in competitive industries. (Rowles 2025, 97-98) Paying for top results is not a guarantee of success, as Google will consider the relevance and quality of webpages when determining placement.

Ultimately, search is a constantly evolving space, which requires businesses to balance their SEO, user experience, and strategic PPC efforts to match this evolution. By understanding how search engines rank content, how consumer audiences interact with search results, and how paid search results fit into the broader marketing strategy, businesses can maximise their online presence and ensure long-term, permanent digital success.

2.2 Biases in Search Engines

The neutrality of search engines has long been debated, with companies alleging that they are unfairly penalised or promoted by search algorithms. This issue was already highlighted in 2009 by Adam Raff, co-founder of Foundem, who claimed that Google was deliberately demoting his company's results in favour of its own services. (Maillé et al. 2022, 3) Such claims have contributed to ongoing discussions about the presence of biases in search results across diverse fields of information retrieval, and various biases have emerged as central concerns.

Search engines serve as gateways to knowledge and vast amounts of online content, offering users quick and easy access to information. However, while they enhance accessibility, these platforms also introduce biases that can influence user search behaviour, create knowledge disparities, and ultimately lead to suboptimal decision-making for information seekers. (Gao & Shah 2021, 1) These biases affect both visibility and the ranking of content, as search algorithms balance multiple factors, including computational algorithms and external factors, like SEO strategies. Given the growing reliance on search engines for information retrieval, it is crucial to improve transparency in how search engines function.

People are exposed daily to some degree of biased content – among the most notable biases are popularity and position bias. Algorithms that favour popular items are found everywhere online – they help users select from many results presented to them. Popularity bias occurs when algorithms favour well-known items regardless of their inherent quality, while position bias is the users' tendency to trust and select top-ranked results simply because they appear first. (Ciampaglia, Nematzadeh, Menczer & Flammini 2018, 1) These biases complement and reinforce one another: higher-ranked items attract more clicks, which algorithms tend to interpret as increased popularity, further boosting their positions and potentially reducing content diversity.

2.2.1 Position Bias

Position bias is a pervasive phenomenon evident on search engine results pages and other interfaces that list items, such as product search pages. Position bias can be found everywhere – it is demonstrated in horizontal and vertical listings, brand and delivery filters, and page navigation. (Désiguad 2024) Essentially, position bias influences how users notice and prioritise items, often leading them to focus on what is most prominently displayed.

On Google's SERP, the top-ranked result typically receives almost twice as many clicks as the second result, with the second result in turn garnering twice the clicks as the third. (Désiguad 2024) This pattern highlights how the order in which the results are presented can significantly shape user behaviour, as users tend to assume that higher-ranked items are more relevant and trustworthy.

The ranking order of search results is determined by algorithms that evaluate content relevance and authority based on various factors. Although these algorithms may adjust ranking based on external variables, such as geographical location, the consistent finding is that users disproportionately favour top-listed results. (Heinze et al. 2025, 236) This reinforces the idea that the design and ordering of search results play a critical role in steering consumer choices, making users favour higher-ranked results and therefore, assume that top listings are most relevant and trustworthy.

Search engines showcase a phenomenon where people are likelier to trust search engines to assign higher ranks to the results that are best suited to their needs, despite not knowing how the results are ranked. Search engines produce consistent browsing behaviour of users only choosing the top results due to their basic design of the list. (Epstein & Robertson 2015, 1) When items are presented in a list of things, such as search results, people are rarely able to fairly evaluate all of the items in the list. Throughout centuries of research, it has been proven that an item's position on a list does have a powerful and persuasive impact on the person's recollection and evaluation of that item. (Epstein & Robertson 2015, 1)

Order effects impact a person's recall and evaluation of items in a list – primacy refers to items at the beginning of a list, and recency refers to those at the end. Primacy order effects have been shown to influence user decision making in many contexts, and online, primacy has been shown to impact the way users go through websites and influence products that receive recommendations. Search engine results that are highly ranked on the SERPs maintain a strong influence because they attract the gaze of the users, even if there are far better results in lower-ranked positions. The order of search results, the order effect of the SERP, has a particularly strong influence during online search. (Epstein et al. 2017, 3)

2.2.2 Search Engine Manipulation Effect

Search engines exert a unique influence over their users compared to traditional media, such as newspapers and television, and play a crucial role in shaping consumer decisions and perceptions. (Epstein et al. 2017, 3) One significant concept in this domain is the Search Engine Manipulation Effect (SEME). First introduced by Epstein and Robertson (2015), SEME describes how the ranking of search engine results can alter user preferences, attitudes, and beliefs. In their original study on political opinions, the researchers found that ranking bias could influence voter preferences and even shift election outcomes, with participants largely unaware of this manipulation. (Epstein & Robertson 2015, 1)

As search engines increasingly rely on algorithms that rank, filter, and personalise content, their impact on everyday decision-making grows. SEME demonstrates that algorithmic biases, SEO strategies, and paid advertising can all contribute to the importance of certain results. (Epstein & Li 2023, 4) Users generally assume that top-ranked search results are based solely on relevance, credibility, and quality. However, these rankings are influenced by multiple factors, leading users to place disproportionate trust in the highest-ranked results, even when lower-ranked options might be more relevant or reliable. (Epstein et al. 2017, 3)

From a consumer perspective, SEME highlights the need for greater digital literacy and awareness of search engine ranking mechanisms and biases that may appear in the results. Research done by Epstein and Robertson (2017, 12) gives further evidence that forewarnings or alerts about search ranking bias can significantly suppress SEME and increase the proportion of awareness that users show to bias. However, the awareness of ranking bias suppresses SEME only when it occurs together with a bias alert. (Epstein & Robertson 2017, 13)

SEME is closely linked to position bias, reinforcing the notion that consumers tend to favour higher-ranked results simply because of their position on the SERP. This is particularly significant in the e-commerce field and context, where businesses invest heavily in SEO and SEM strategies to ensure their products appear at the top, thereby influencing consumer choices through increased visibility and positioning alone.

2.3 Consumer Behaviour

A deep understanding of consumer behaviour is essential for effective marketing. Marketers must grasp how consumers think, feel, and act to ensure that they can deliver clear value to their target audience. (Kotler, Keller & Chernev 2022, 78) Consumer buying behaviour is influenced by a range of factors – cultural, social, and personal. Cultural factors, in particular, play a fundamental role in shaping consumers' perceptions, desires, and needs. Culture, which encompasses the beliefs, values, and norms shared by a group, is passed down through generations and significantly carves consumer behaviour. (Kotler et al. 2022, 79; Kumar & Pansari 2016, 5)

Social influences and personal characteristics further contribute to how consumers make purchase decisions. Social groups affect beliefs and decision-making processes, while personal factors such as age, life cycle stage, occupation, economic circumstances, personality, and lifestyle shape individual buying patterns. (Kotler et al. 2022, 81-83) For instance, consumers are more inclined to choose and use brands whose brand personality aligns with their self-concept and the way they view themselves, even if the match may be based on how the consumer would like to view themselves. Moreover, a consumer's lifestyle – whether they are money- or time-constrained –along with their economic environment, can significantly determine consumption patterns. (Kotler et al. 2022, 83; Kumar & Pansari 2016, 5)

The consumer decision journey outlines the process from recognising a need to then searching for information and ultimately making a purchase. Research has shown that the information search done by consumers is often limited, typically evaluating a single source or brand before deciding on their purchase. (Kotler et al 2022, 91-92) Additionally, four key psychological processes, such as motivation, perception, learning, and memory, play a crucial role in shaping consumer responses. Marketers must be able to identify these psychological processes and identify the circumstances that will trigger the need of a consumer. This is done by gathering information and seeking trends and patterns of consumers, which then allows them to develop marketing strategies and effective advertising campaigns that will pique the interest of the consumer. (Kotler et al. 2022, 84-91)

2.3.1 Consumer Behaviour in Online Shopping

The arrival of digital technology has fundamentally reshaped consumer behaviour, shifting preferences from traditional stores to online channels, mobile applications, and smartphone-led digital technologies. Noticeably, consumers aged 18-40 have consistently driven the growth of online shopping, which has made it a critical area for understanding how search engine results influence purchase decisions. (Agrawal 2022, 880)

Consumer attention, which is the allocation of processing capacity to a stimulus, plays a crucial role in online shopping. This attention may be both voluntary, where consumers purposefully seek out information, and involuntary, where something unexpected captures their focus. (Kotler et al. 2022, 88) Given the vast number of ads and brand communications consumers encounter daily, they are likely to screen out stimuli that do not immediately capture their interest and engage in something called selective attention. For marketers, this means identifying the precise cues that will attract a consumer’s attention, particularly within the highly competitive online environment. (Kotler et al. 2022, 88)

Online search behaviour varies significantly based on how product information is presented. For instance, when search engines and e-commerce platforms display product alternatives in a ranked order of predicted attractiveness, consumers are less likely to conduct extensive searches beyond the top results. Studies have demonstrated that most consumers rarely venture beyond the first page of search results, underscoring the influence of position bias on consumer decision-making. (Kotler et al. 2022, 93) Eye-tracking research further supports this finding, revealing that users allocate significantly more attention to the top-ranked items on a search engine results page. (Lewandowski & Schulteiß 2023, 1485) These studies allow for a better understanding of consumer behaviour in online shopping and how consumers use search engines. It can also allow a look into the influence of positioning within search engines affect consumer behaviour.

Decades of research have established that an item’s position in a list affects its recall and evaluation. (Epstein & Robertson 2015, 1) In the context of online shopping, this means that products appearing at the top of search results are more likely to be clicked, while lower-ranked items receive little attention. This phenomenon, central to position bias, helps explain why consumers often select the first few options presented to them, even if alternative products further down the list might better meet their needs. Users are less likely to go further down the list and keep their focus on the top results.

Kotler et al. (2022, 92) establish that consumers will start their search behaviour often in a search state called the heightened attention, which is the level a consumer is simply willing to be receptive to information about a product. Following this, the consumer will enter an active information search, where they look for reading materials about purchases, go online, and utilise search engines to find further information. Nonetheless, Rogers (2019) says that a concept called search engine attention effect has been found, where fewer and fewer search engine result pages are browsed. Consumers are beginning to lose the need to seek further information, allowing the search engine to determine the level of search behaviour they exhibit.

The COVID-19 pandemic caused a change in shopping behaviour – it affected what consumers purchase and how consumers purchase. E-commerce sales increased drastically at rates beyond the originally anticipated amounts. Consumers began to become less loyal to brands, but chose products based on availability, and are now less likely to wait for products to be restocked. (Hair Jr., Ortinau & Harrison 2024, 53) Consumers are more reliant on search engines and the internet for their purchases.

2.3.2 Consumer Behaviour Across Generations

Generational cohort analysis provides valuable insights into consumer motivations and purchasing decisions, as these are often shaped by shared values, beliefs, and technological familiarity. Studies have highlighted notable differences in online shopping behaviour across generations, with factors such as digital literacy, social media influence, and price sensitivity playing key roles in shaping purchasing habits. (Agrawal 2022, 881) Understanding these generational differences is essential for businesses, as it allows them to tailor marketing strategies that align with the specific preferences and expectations of each age group. Furthermore, these differences may also impact how consumers interact with search engines, influencing their trust in search results and the way they assess relevance.

Younger consumers increasingly will prefer digital shopping due to its convenience, access to extensive product information, and higher engagement with emerging trends. They actively seek out reviews, ratings, and peer opinions before making purchasing decisions, utilising search engines and social media to explore brands and products. (Agrawal 2022, 880) Additionally, younger consumers tend to exhibit a more immersive digital buyer journey, enjoying the interactive aspects of browsing, discovering new trends, and connecting with the brand and other consumers. This contrasts with older generations, who may rely more on traditional decision-making processes and place higher trust in established search rankings without critically evaluating their placement.

For marketers, these behavioural distinctions are crucial when designing search engine and digital marketing strategies. Young consumers' reliance on search engines for shopping choices makes them more susceptible to position bias, as they are likely to select top results due to convenience. Older consumers' trust placed in search results makes them keener to believe the top results and further perpetuates position bias. By recognising how different generations interact with search engines and perceive results credibility, businesses may optimise their SEO and SEM strategies accordingly to effectively reach their target audience and influence purchasing behaviour.

2.3.3 Search Engine's Impact on Consumer Choices

A basic assumption among users is that search engines provide the most relevant and trustworthy results for their queries. Users rely on search engines to filter information and present the best possible answers, often selecting from the top results on the SERP. (Lewandowski & Schulteiß 2023, 1026) However, while users generally trust search engines to deliver unbiased results to their queries, they may not be fully aware of the ranking biases that influence what they see. This raises the question of whether consumers recognise how search engine algorithms, commercial interests, and other factors shape their search experiences.

Consumers will frequently use search engines for various purposes, including product research and online shopping. Studies show that users trust search engines more than other digital sources, particularly when comparing them to social media. (Lewandowski & Schulteiß 2023, 1027) This trust extends to commercial searches, where users assume that the top-ranked results are not only more relevant but also more credible. However, this perception could be misleading, as ranking algorithms prioritise certain results based on factors such as SEO strategies, ad placements, and previous user interactions, rather than pure relevance. (Lewandowski & Schulteiß 2023, 1028) As a result, users may be unknowingly influenced by position bias, meaning they are more likely to click on higher-ranked results without critically assessing their placement.

The 2024 Eurobarometer survey on digital technologies found that 86% of respondents believe it is important to improve transparency and security in digital technologies, with 44% considering this very important. (European Commission 2024, 40) This highlights growing consumer concern over how digital systems, including search engines, operate and influence decision-making. As search engines play an increasingly central role in information access, there is a demand for greater transparency regarding how search rankings are determined. If users remain unaware of ranking biases, their online shopping decisions may be disproportionately influenced by search engine algorithms rather than their independent research. Users need to understand how search engines may favour some results and influence what users get to see. This affects the results that the users will pay attention to and which results they select. (Lewandowski & Schulteiß 2023, 1025)

The tendency for users to select top search results can be classified as satisficing, a decision-making process where users settle for the first option that meets their needs rather than conducting extensive research. (Lewandowski & Schulteiß 2023, 1027) This behaviour is especially evident in online shopping, where consumers often click on the highest-ranked product listings, assuming them to be the best available options. Search engines, like Google, optimise their algorithms to keep users engaged, for example, by prioritising fast-loading pages to retain attention and prevent users from leaving the platform. (Rowles 2025, 83) These design choices reinforce position bias by making it more convenient for users to interact with the top results, further limiting their exposure to potentially better alternatives found further down the SERP.

3 Research Methodology

The following chapter introduces the research methodology used to conduct the study, which is explained in Chapter 4. The author first goes through the different phases in the research design and how they are linked to the investigative questions presented earlier. Lastly, the data collection, management, and analysis are explained thoroughly for the reader to understand.

3.1 Research Design

This thesis aims to examine how position bias in organic search engine rankings influences consumer behaviour, with a particular focus on generational differences between younger and older consumers. Figure 1 illustrates the research design process. Phase 1 involves conducting the theoretical framework that has been explored in the previous chapter. The theory explored the needed theory and concepts to further understand the analysis of the data collected. It introduces the theory behind search engines, biases, and consumer behaviour, all related to the investigative questions.

The second phase of the research is data collection to answer the investigative questions. In this phase, the data collected can be organised and analysed. Once the data was collected, the analysis of the results could be started, and the multiple investigative questions could be effectively answered – this is phase 3. This means further understanding of position bias in search engine ranking influence and the generational differences. In the final phase, conclusions are formed based on the previous analysis and the theory explored in phase 1. These conclusions allow for further research recommendations and reflection upon the research process.

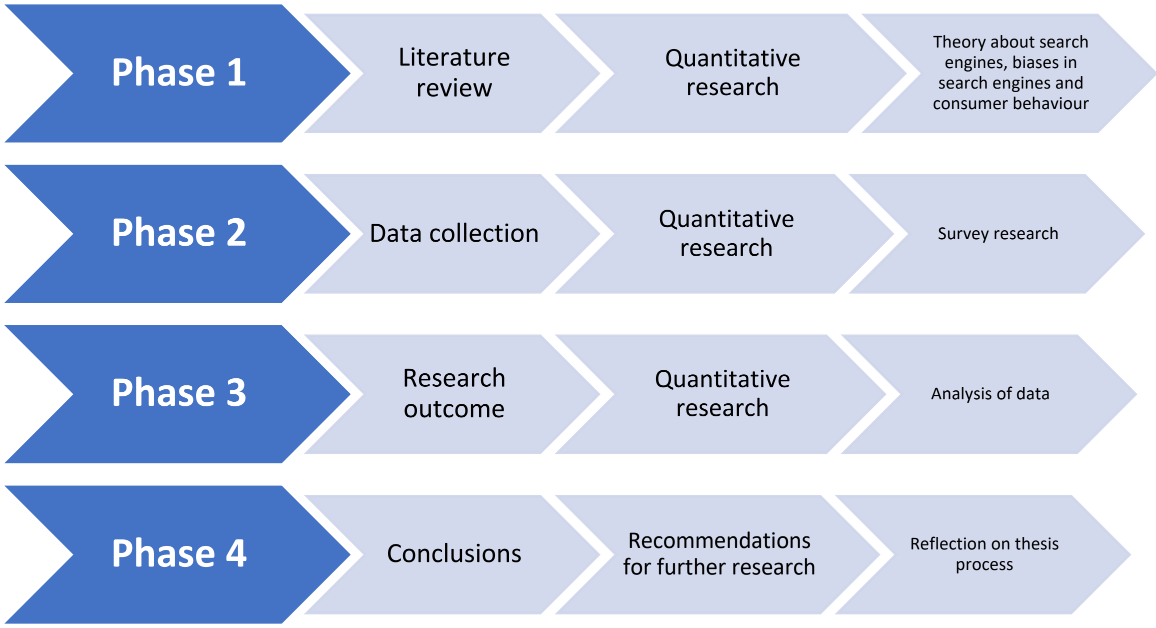

Figure 1. Research Design & Process

3.2 Research Methods

This thesis employs a quantitative research approach, which focuses on variables that can be measured and statistically analysed, often using larger samples. (Cozby & Bates 2024, 132) Quantitative methods are particularly suitable for investigating patterns and trends in consumer behaviour related to search engine result rankings, allowing the study to generalise findings from the collected data.

This thesis utilises an online survey-based methodology to gather data from a broad and diverse sample of respondents. Surveys provide a structured way to collect standardised responses on facts, demographics, and attitudes, which makes them an ideal method for comparing generational cohorts' search behaviours and perceptions of position. As society increasingly seeks insights into behavioural trends, surveys have proven an effective way to analyse relationships among variables and track changes over time. Online surveys are the most frequently used method for research in the marketing field and are used to gain meaningful insights into behavioural relationships. (Cozby & Bates 2024, 151; Hair et al. 2024, 123)

A structured, self-administered online survey was chosen because it enables efficient data collection across different age groups. The survey is designed to measure key constructs, including consumer trust in search engine rankings, the extent of position bias, generational differences in search behaviour, and awareness of search engine bias. These variables are critical for understanding how ranking positions influence consumer decision-making processes.

Alternative research approaches, such as qualitative approaches like interviews or focus groups, were considered but ultimately rejected due to their limited generalisability and challenges in analysing large-scale trends**.** (Ghauri & Gronhaug 2010, 121) A mixed-methods approach was also ruled out to maintain clarity in data interpretation and avoid unnecessary complexity. To ensure reliability, the survey employs a standardised structure with consistent wording and response formats, making the instrument replicable under similar conditions. (Ghauri & Gronhaug 2010, 119-120) Validity is addressed by basing survey questions on established literature explored in the theoretical framework about consumer search behaviour and position bias, thereby ensuring content and construct validity. Through these measures, the research aims to produce reliable and valid findings that accurately reflect consumer perceptions of search engine rankings across different generational cohorts.

3.3 Data Collection

Surveys refer to a method of data collection that utilises either questionnaires or interview techniques to record the behaviour of respondents. Surveys are effective tools to gather opinions, attitudes, and descriptions, as well as to capture cause-and-effect relationships. Surveys are among the most popular data collection methods used in business studies, and the major types of surveys are either descriptive or analytical. (Ghauri & Gronhaug 2010, 118-119)

Data was collected through an online survey distributed via various digital channels. The target population comprised consumers who use search engines for retail shopping. The sampling process employed non-probability sampling methods, specifically convenience and snowball sampling. Initially, the survey was shared with participants from existing networks and social media platforms, utilising convenience sampling to reach an audience. Convenience sampling allows for large numbers of respondents within a short time frame. (Hair et al. 2024, 156) Respondents were then encouraged to forward the survey to their contacts, thereby employing a snowball sampling strategy. Snowball sampling relies on participants to identify others who may possess attributes needed for the sample and allows for a wider respondent rate. (Cozby & Bates 2024, 171) The combination of these two sampling methods was appropriate, as it allowed for a fast data collection from diverse generational cohorts.

The survey was structured with a focus on collecting standardised data on consumer behaviour and perceptions related to search engine rankings and position bias. It utilised a range of question types. The survey included structured questions, rating scale questions such as Likert scales and ordinal scales, and a few unstructured questions. (Hair et al. 2024, 190-213) These questions measure variables such as trust in search engine results, frequency of clicking on top-listed links, and awareness of search engine bias. Questions were grouped into themes covering demographic information, search behaviour, and attitudes toward search engine results, ensuring that all relevant constructs were addressed systematically.

To ensure high data quality, the survey was pilot tested with a small subset of respondents before full deployment to test the question clarity, reliability, and survey structure. Using both convenience and snowball sampling allowed for a wider reach in respondents, but it is acknowledged that there are limitations in terms of generalisability due to this.

3.4 Data Management and Analysis

This thesis employed a quantitative data analysis to examine the generational differences in consumer behaviour related to search engine result rankings. The data was collected through a structured online survey done on Webropol, and the analysis was done on Microsoft Excel. Both were effective tools for managing and statistically analysing the structured survey data.

The analysis process followed a clear approach to ensure transparency. First, the respondents were grouped into three generational cohorts for comparative analysis: 16-34 years, 35-44 years, and 45-69 years. These groupings were based on response distribution and the need for balanced sample sizes across groups.

Descriptive statistics were used to provide an overview of the respondents' behaviour and attitudes. To test for statistically significant differences between generational groups, one-way ANOVA (Analysis of Variance) tests were conducted on relevant survey questions, particularly those using Likert scale responses. One-way ANOVA compares the means of two or more independent groups to determine whether there is statistical evidence that the means are significantly different. One-way ANOVAs are commonly used to test statistical differences among the means of two or more groups. (Kent State University n.a.)

Data reliability was supported through the use of a standardised questionnaire format, which ensured consistency in responses across participants. Validity was strengthened by designing the survey questions based on existing literature on consumer search behaviour and position bias. However, some limitations must be acknowledged – the sample was collected using convenience and snowball sampling, which can reduce the generalisability of the results due to potential selection bias.

Despite these limitations, the analysis provides meaningful insights into how generational cohorts differ in their interaction with search engine results, offering a valuable contribution to understanding consumer behaviour in the context of digital search environments.

4 Survey

This chapter will analyse the results from each question presented in the survey. By doing so, the author aims to find answers to investigative questions presented earlier in this thesis.

4.1 Demographic Characteristics

The survey received a total of 133 responses. All of the 133 respondents gave their consent in the first survey question to continue. Respondents were asked to indicate their age group, which serves as the primary demographic variable for this study. The distribution across age groups is presented in Figure 2 below:

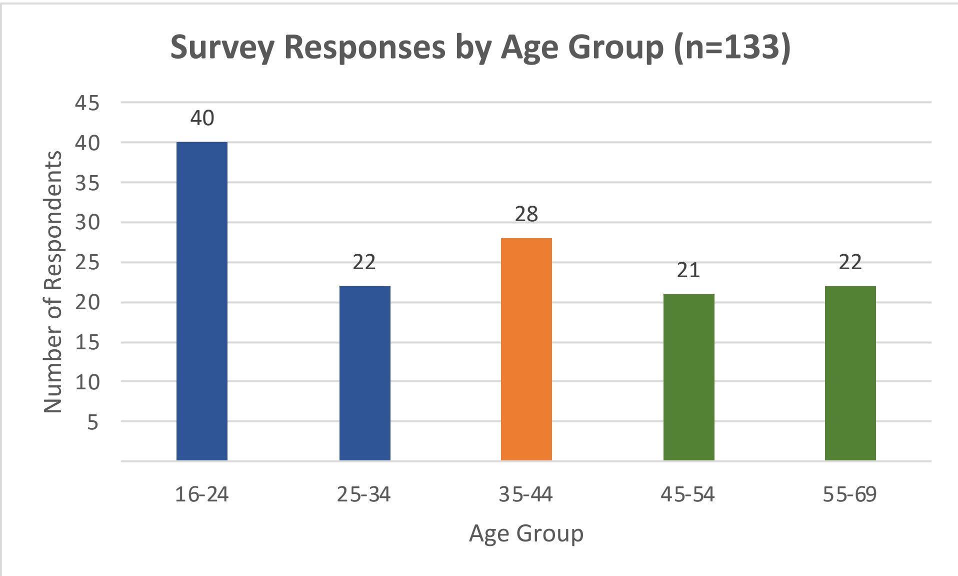

Figure 2. Survey Responses by Age Group (n=133)

To simplify generational comparisons in the analysis phase, the five original age categories were combined into three broader groups:

- Group A (16-34 years) – younger consumers
- Group B (35-44 years) – middle-aged consumers
- Group C (45-69 years) – older consumers

These groupings allow for clearer comparisons of generational differences in search behaviour and awareness of position bias, which are central to the research questions. These groupings allow for easier generalisations.

4.2 General Search Behaviour and Trust in Rankings

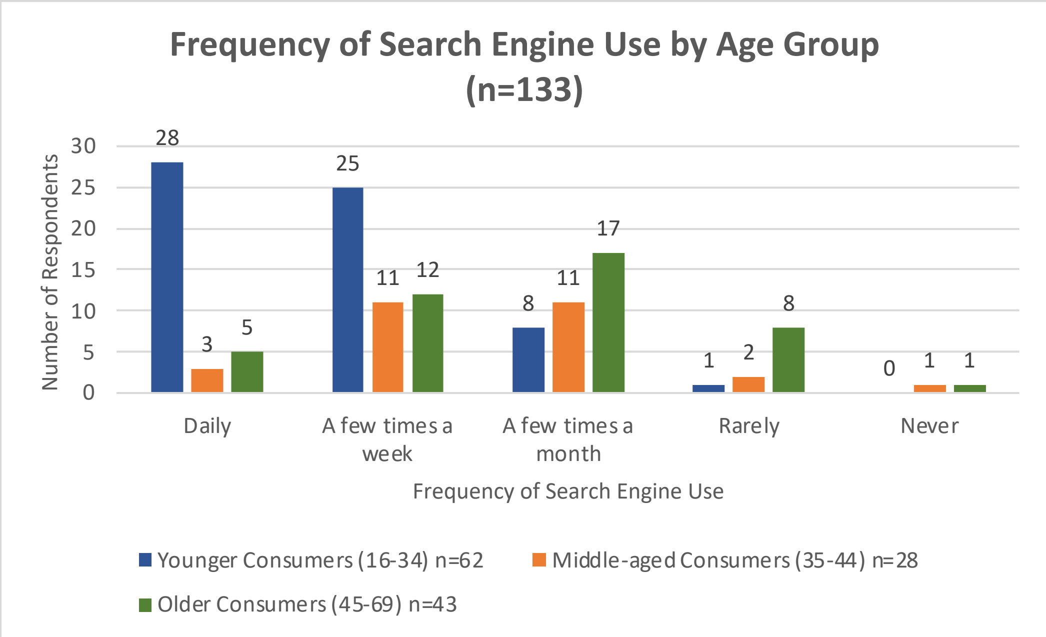

Figure 3. Frequency of Search Engine Use by Age Group (n=133)

As depicted in Figure 3, a total of 36 respondents (n=36) reported using search engines daily to find information on retail or product categories, with the majority of these respondents coming from the young consumers (16-34 years) group. Most responses, with a total of 48 respondents (n=48), reported they use search engines a few times a week. On the other hand, more infrequent use is more common among older consumers (45-69 years) as reflected in the “rarely” and “never” categories.

Position bias, which relies on users engaging primarily with the top-ranked results on SERPs, is closely tied to search frequency. Frequent users can develop search habits that reinforce further reliance on these top results, which potentially intensifies the effect of position bias on their decision-making. At the same time, infrequent users may lack familiarity with search engines and how they function and are therefore more likely to assume the top results are inherently more trustworthy. This makes infrequent users equally, if not more, vulnerable to position bias. Thus, search engine frequency across age groups provides meaningful context for understanding the extent and variability of position bias among consumers.

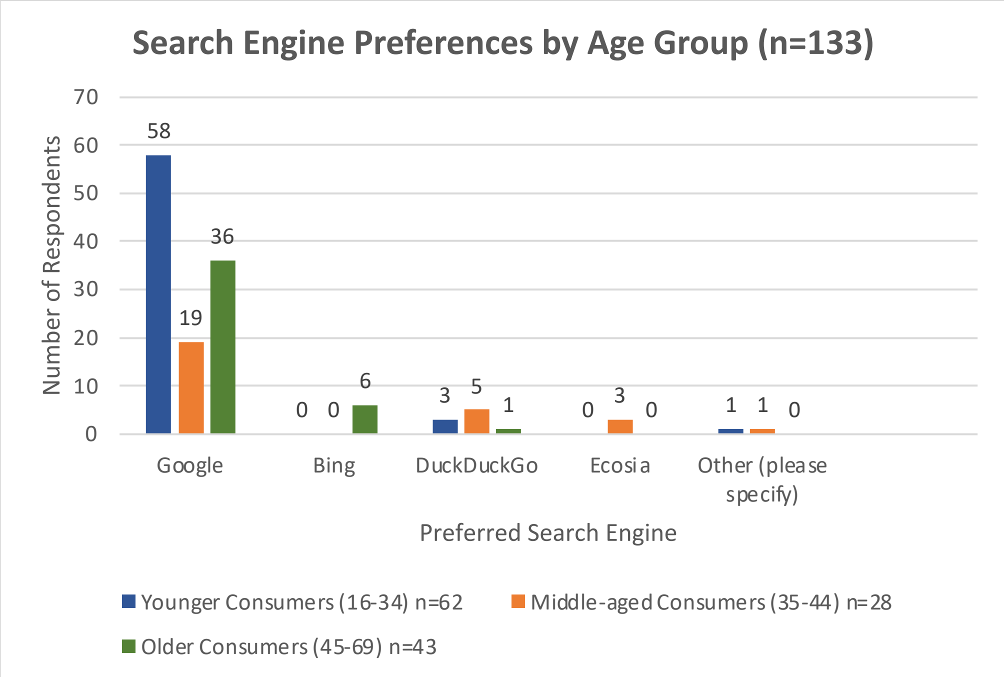

Figure 4. Search Engine Preferences by Age Group

Figure 4 highlights that Google was by far the most preferred search engine across all age groups in this study, with 113 out of 133 respondents selecting it. This finding aligns with the global trend noted earlier, confirming Google's dominance not only on a global level but also among this survey's respondents. Notably, alternative search engines such as Bing, DuckDuckGo, and Ecosia were selected by only a small minority, with the majority of those choices coming from older or middle-aged consumers.

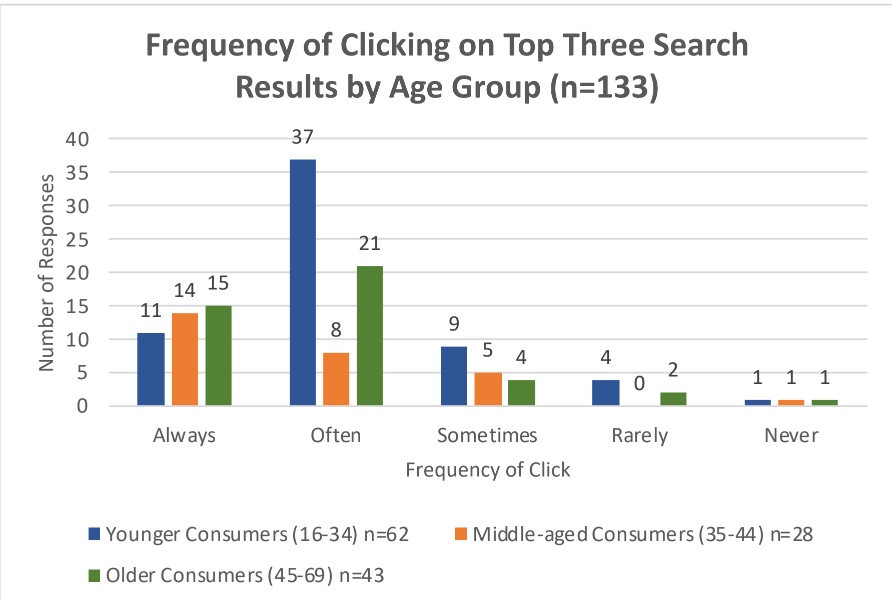

Figure 4. Frequency of Clicking on Top Three Search Results by Age Group (n=133)

As seen in Figure 5, the majority across all age groups report clicking on one of the top three search results at least “often”. Younger consumers (16-34 years) show the highest proportion in the “often” category, whereas middle-aged consumers (35-44 years) and older consumers (45-69) show slightly higher selections in the “always” category.

To further understand the click behaviour of generational cohorts, descriptive statistics were used by assigning a numerical value to each answer option (5 = Always, 1 = Never). The average click frequency was calculated for each generational cohort. The results revealed that the middle-aged consumers had the highest average (M = 4.21), followed by older consumers (M = 4.09), and younger consumers (M = 3.85). This suggests that older users may place more trust in the top-ranked results compared to younger users and are more likely to click on the higher-ranked results.

Table 2. One-Way ANOVA Results for Frequency of Going Past the First Page of Search Results by Age Group

ANOVA						
Source of Variation	**SS**	**dF**	**MS**	**F**	**P-value**	**F crit**
Between Groups	13.63	2	6.81	7.42	0.0009	3.07
Within Groups	119.37	130	0.92			
Total	**132.99**	**132**				

A one-way ANOVA was performed to determine whether there were significant differences among the three age groups regarding the frequency with which they would go past the first page of search results. Table 2 displays the ANOVA results done on Excel. The analysis indicated a statistically significant effect of age group on this particular search behaviour ($F(2,130) = 7.42$, $p = 0.0009$). The calculated F-value exceeds the critical value ($F\ crit = 3.07$), suggesting that the means for at least one of the groups differ significantly.

Specifically, the between-group variation (SS = 13.63) relative to within-group variation (SS = 119.37) produced mean squares (MS) of 6.81 and 0.92, thus resulting in the overall significant F-statistic. This suggests that the tendency to go past the first page of search results differs by age group. For instance, descriptive statistics show that younger consumers may be more inclined to navigate through multiple pages, whereas older consumers might be less likely to do so – this pattern could be linked to reliance on search engine rankings.

To further investigate the significant difference found in the one-way ANOVA ($F(2,130) = 7.42$, $p = 0.0009$), a Least Significant Difference (LSD) post hoc test was conducted to determine which age groups differed significantly in how often they go past the first page of search results. The analysis revealed the following: younger consumers ($M = 2.29$) were significantly more likely to go beyond the first page compared to middle-aged consumers ($M = 1.46$), $p < 0.001$. Older consumers ($M = 1.91$) also reported going past the first page more frequently than middle-aged consumers, $p < 0.045$. The difference between younger and older consumers was statistically insignificant ($p = 0.206$).

The presence of these generational differences implies that the way users interact with search results and how they are influenced by result positioning varies across age groups. This variation is important because it highlights that both familiarity with digital search environments and trust in the presented ranking order may affect whether or not individuals venture beyond the first page when searching for products.

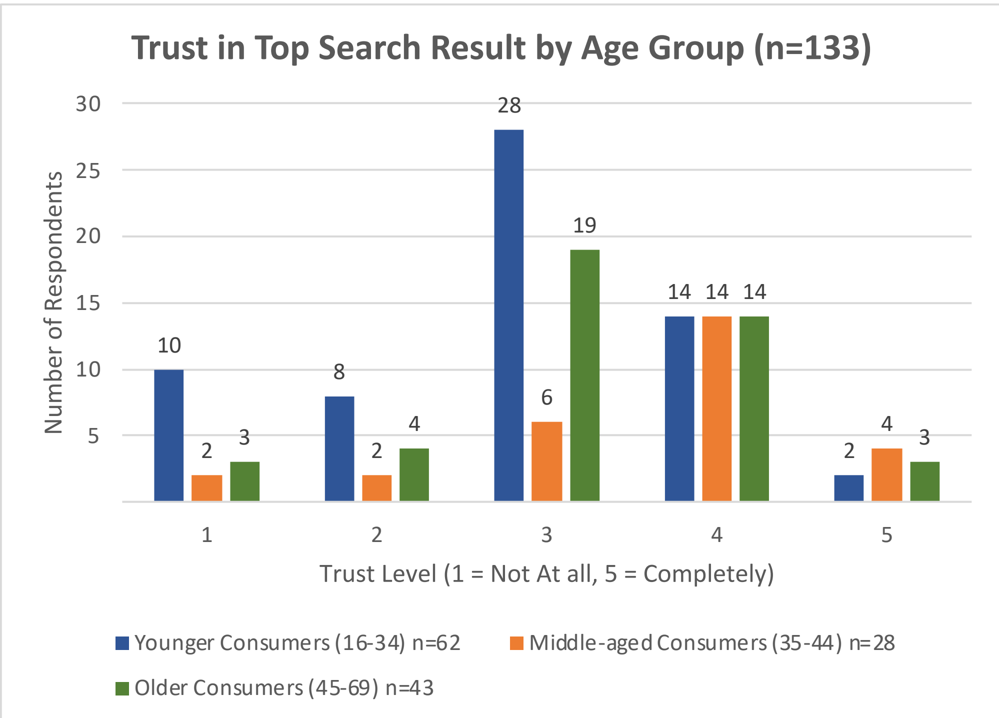

Figure 5. Trust in Top Search Result by Age Group (n=133)

Figure 6 illustrates how much respondents across different age groups trust that the top search result is the best option, on a scale from 1 (not at all) to 5 (completely). This question was done in a Likert rating scale question form in the survey, Younger consumers (16-34 years) show the lowest average trust score (*M* = 2.8), suggesting a more critical or sceptical view of search result rankings. Middle-aged consumers (35-44 years) report the highest trust (*M* = 3.6) from all groups. Older consumers (45-69 years) fall in between (*M* = 3.2), with responses more evenly distributed across the scale. For instance, 64.3% of middle-aged respondents rated their trust as 4 or 5, compared to only 25.9% of younger consumers.

These results imply that younger users may be more aware of search engine algorithms or are less likely to assume top-ranked results are the best, whereas middle-aged users appear to place more trust in ranking credibility in search engines. This could further imply that middle-aged users are more likely to be influenced by the result positioning of search results and further perpetuate position bias. With the increased tr

4.3 Awareness and Perceptions of Search Engine Bias

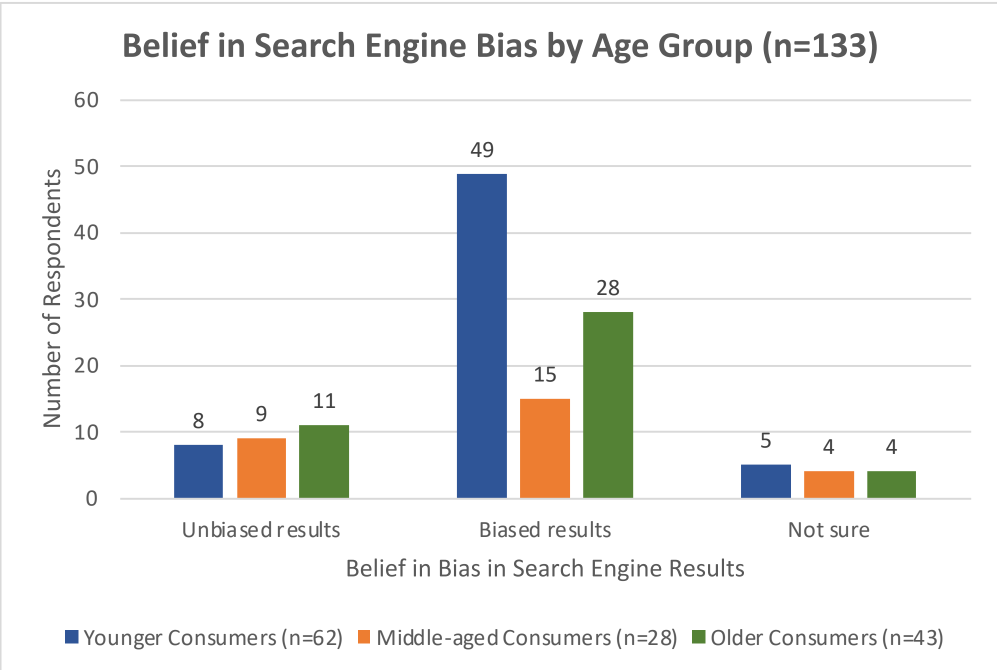

Figure 6. Belief in Search Engine Bias by Age Group (n=133)

As shown in Figure 7, there is a clear generational divide in perceptions of search engine bias. The majority of younger consumers, around 79%, believe that search results are influenced by external factors and have biased results, while older consumers, around 65%, show slightly less scepticism towards search results. Middle-aged consumers had a higher belief in search results being unbiased, despite still showing slight scepticism towards the results, too.

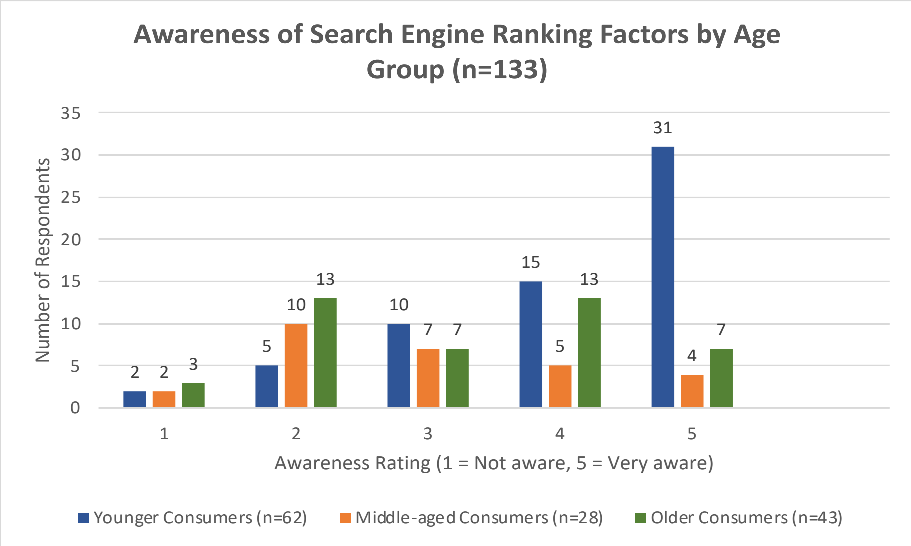

Figure 8. Awareness of Search Engine Ranking Factors by Age Group

Figure 8 shows the complete distribution of responses to the question "Are you aware that search engines rank results based on multiple factors, such as search engine optimisation, personalisation, and algorithmic biases?" across the three age groups. The graph reports that a larger proportion of younger consumers provided higher ratings (4 or 5) compared to middle-aged or older consumers.

Table 3. Awareness of Search Engine Ranking Factors by Age Group (Average and CES)

Age Group	**Average Awareness (M)**	**CES (4–5 responses)**
Younger Consumers (16–34)	*M* = 4.1	74.2%
Middle-aged Consumers (35–44)	*M* = 3.0	32.2%
Older Consumers (45–69)	*M* = 3.2	46.6%

Table 3 summarises the data by presenting the average awareness scores (*M*) and the Customer Effort Score (CES), which represents the percentage of respondents who selected 4 or 5, for each age group. The table indicates that younger consumers have a notably higher average score (*M* = 4.1, *CES* = 74.2%), which suggests that younger consumers are more aware of the factors influencing search engine results. In contrast, middle-aged consumers recorded the lowest average score (*M* = 3.0, *CES* = 32.2%), while older consumers showed a moderate level of awareness (*M* = 3.2, *CES* = 46.6%).

Table 4. One-Way ANOVA Comparing Awareness of Search Engine Ranking Factors Across Age Groups

ANOVA						
Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Between Groups	24,64	2	12,32	8,29	0,0004	3,06
Within Groups	202,11	136	1,49			
Total	**226,75**	**138**				

A one-way ANOVA was performed to determine whether there were significant differences among the three age groups in the awareness of search engine ranking factors. Table 4 displays the ANOVA results done on Excel. The analysis revealed a statistically significant difference between groups ($F(2, 136) = 8.29$, $p < 0.001$).

Following the ANOVA results, which indicated a significant difference between the age groups ($F = 8.29$, $p = 0.0004$), a post-hoc Least Significant Difference (LSD) test was performed to identify which specific pairs of groups differed significantly. The analysis revealed that the younger consumers ($M = 3.93$) demonstrated significantly greater awareness compared to the middle-aged consumers ($M = 2.96$), $p < 0.001$. Younger consumers also reported significantly higher awareness than older consumers (*M* = 3.19), $p < 0.01$. However, the difference between middle-aged and older consumers was statistically insignificant ($p = 0.31$).

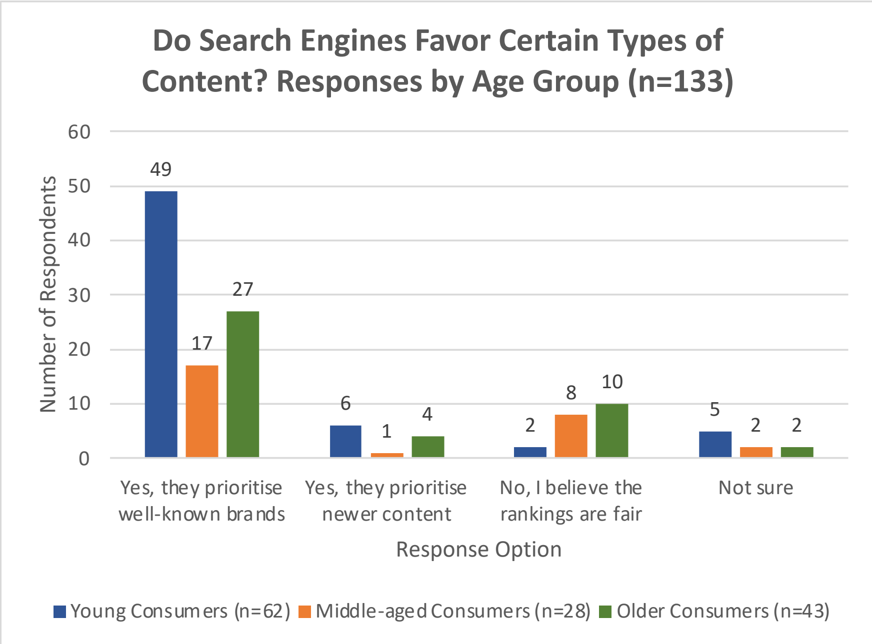

Figure 9. Do Search Engines Favour Certain Types of Content? Responses by Age Group (n=133)

The majority of respondents across all generations believe search engines favour well-known brands, with 79.0% of younger consumers, 60.7% of middle-aged consumers, and 62.8% of older consumers selecting this option, as seen in Figure 9. Only a small fraction think newer content is prioritised, and even fewer consider the rankings to be entirely fair. A handful of respondents remain uncertain. These findings highlight widespread scepticism about the neutrality of search results and generational variations in the types of bias users believe are most prevalent.

4.4 Generational Differences in Search Behaviour

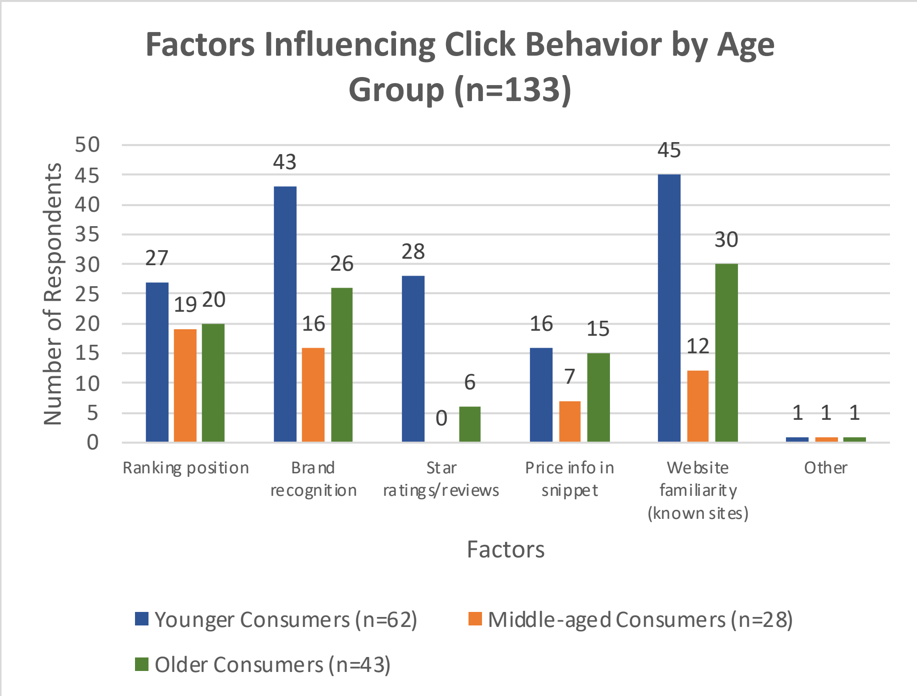

Figure 10. Factors Influencing Click Behaviour by Age Group (n=133)

To understand which factors influence consumers' decisions to click on a search result the most, respondents were asked to select up to three options from a list of potential motivations, including ranking position, brand recognition, star ratings/reviews, price information, website reputation, and other factors. As shown in Figure 10, the majority of respondents across all age groups indicated that ranking position is a key influence on their decision-making, with 67.9% of middle-aged consumers, 43.5% of younger consumers, and 46.5% of older consumers selecting this option. This indicates, particularly among middle-aged respondents, that the prominence of a listing is a decisive factor when choosing which search result to click. Brand recognition was also highly influential, particularly among the younger and older consumers. This suggests that a familiar brand name can strongly influence consumer decisions, upholding the role of established brands in online search behaviour.

Other factors, such as star ratings/reviews and price snippets, received lower overall selection, which indicates that these factors may be less pivotal compared to ranking position and brand recognition in driving clicks. Additionally, website reputation was highly regarded with 72.6% of younger consumers, 42.9% of middle-aged consumers, and 69.8% older consumers chose it. This suggests that consumers are attentive to the credibility cues provided by familiar or reputable websites.

Figure 10 emphasises that while ranking position and brand recognition are crucial influences for all groups, there are subtle generational differences. For instance, middle-aged consumers appear particularly focused on ranking position as a reason to click on a search result, which can reflect a deeper trust in the implicit ranking algorithms of search engines.

Table 5. Mean Trust Ratings and CES for Top search Result versus Well-known Brand by Age Group (n=133)

Age Group	**Average Trust Rating (M)**	**Customer Effort Score (CES)**
Younger Consumers (n=62)	2,1	6,50 %
Middle-aged Consumers (n=28)	2,9	25,10 %
Older Consumers (n=43)	2,6	14,00 %

A 5-point Likert scale question was presented to the respondents, asking whether they would trust the top result more than a well-known brand further down the list. The average ratings and CES percentages differ across age groups, as seen in Table 4.

Among younger consumers, the scores were lower (*M* = 2.1, CES = 6.5%), which suggested a general reluctance to trust the top result over a familiar brand. In comparison, middle-aged consumers reported the highest scores (*M* = 2.9, CES = 25.1%) and older consumers slightly lower (*M* = 2.6, CES = 14.0%). These differences indicate that middle-aged consumers may be somewhat more inclined to trust the top result, whereas younger and older groups are generally more sceptical of trusting the top-listed result solely based on its position. Overall, the findings suggest that most consumers, regardless of age, are cautious about automatically trusting the top search result over established brands, which contributes to a more critical perception of search engine rankings.

Table 6. One-Way ANOVA Comparing Age Groups, Trust in Top-Ranked Search Results versus Well-known Brands Lower on the List

ANOVA						
Source of Variation	**SS**	**dF**	**MS**	**F**	**p-value**	**F crit**
Between Groups	15.20	2	7.60	7.65	0.0007	3.07
Within Groups	129.06	130	0.99			
Total	**144.26**	**132**				

To examine whether trust in top-ranked search results over well-known brands further down the list varied by age group, a one-way ANOVA was conducted. The analysis revealed a statistically significant difference between groups, $F(2,130) = 7.65$, $p = 0.0007$ (see Table 6). This suggests that age has a significant effect on whether individuals place more trust in the top-ranked search result compared to a familiar brand appearing lower in the list.

To further analyse the results from the one-way ANOVA ($F(2,130) = 7.65$, $p = 0.0007$), a LSD post hoc test was conducted to determine which age groups differed significantly in their trust in top-ranked search results compared to well-known brands further down the list. The LSD test revealed that younger consumers ($M = 2.10$) were significantly less likely to trust the top result over a known brand compared to middle-aged consumers ($M = 2.90$), $p < 0.001$. Older consumers ($M = 2.60$) also reported significantly lower trust in top-ranked results than middle-aged consumers, $p < 0.01$. However, the difference between younger and older consumers was not statistically significant ($p = 0.13$).

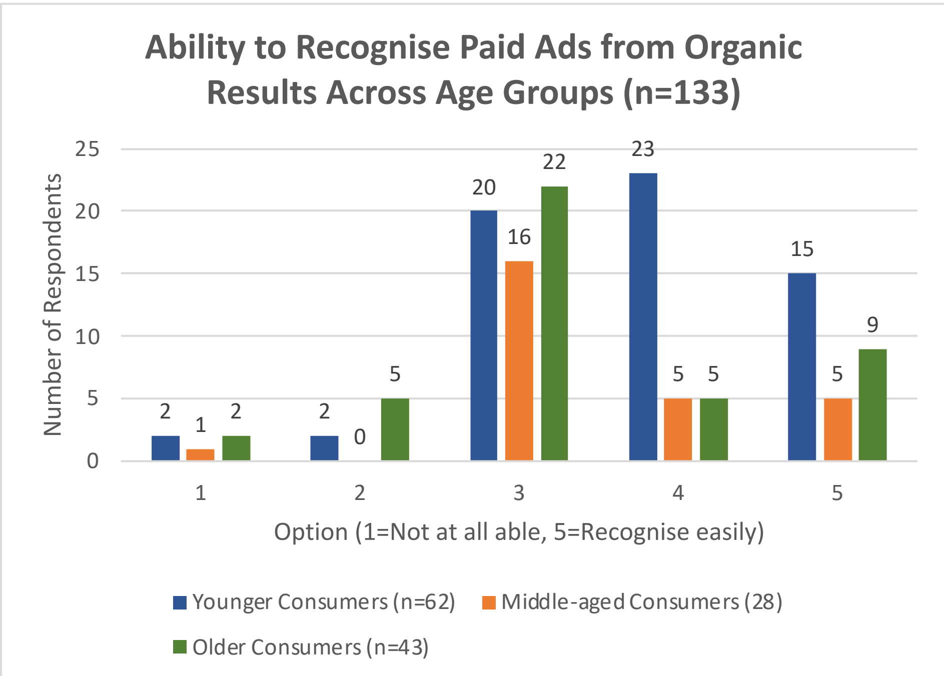

Figure 11. Ability to Recognise Paid Ads from Organic Results Across Age Groups (n=133)

Younger consumers feel most confident in distinguishing paid ads from organic listings, with an average rating of ($M = 3.8$, CES = 61.3%). Middle-aged consumers reported moderate confidence ($M = 3.5$, CES = 37.1%), while older consumers were least confident in recognising paid ads ($M = 3.1$, CES = 32.6%). (see Figure 11) The higher rating among younger cohorts suggests stronger digital literacy and greater familiarity with search interfaces, whereas lower confidence in older cohorts indicates potential vulnerability to ad placements. In general, these results imply that age-related differences in ad-recognition skills could affect how different generations navigate search results and respond to paid versus organic content.

These results indicate that middle-aged consumers are significantly more likely to trust the top-ranked search result over a well-known brand lower in the list compared to both younger and older consumers. In contrast, younger consumers tend to show greater scepticism toward the top rankings, placing more value on brand recognition than search position. Older consumers fall between these two groups, with no significant difference in trust compared to younger consumers. This suggests that trust in search engine rankings varies by age, with middle-aged users appearing more influenced by position bias than other age groups.

4.5 Interaction with Mock SERP Interactions

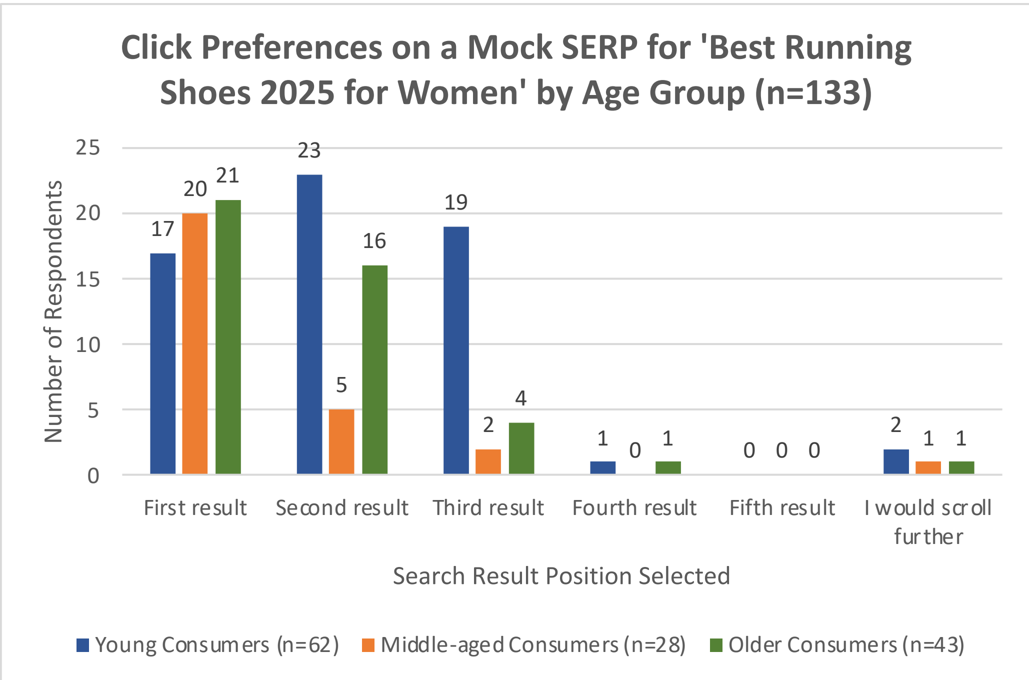

Figure 12. Click Preferences on a Mock SERP for 'Best Running Shoes 2025 for Women' by Age Group (n=133)

Figure 12 displays the results from the first mock SERP question, “Looking at the following search results for ‘Best Running Shoes 2025 for women’, which result would you be most likely to click first?”. The mock SERP mimicked a typical search engine results page with options ranging from the first result to a ‘scroll further’ option.

The data indicates generational differences in click behaviour. Middle-aged consumers predominantly chose the first result (71.4%), whereas younger consumers were more varied in their responses – 27.4% selected the first result and 37.1% opted for the second. Older consumers also showed a preference for the first result (48.9%), although a significant proportion (37.2%) chose the second. These findings suggest that while position bias influences all age groups, middle-aged consumers are the most inclined to favour the top-listed result, with younger consumers exhibiting a more distributed click pattern.

The mock SERP was followed by a question asking respondents to explain why they chose that result. The analysis of responses to the question “Why did you choose that result?” revealed significant insights into the factors driving click behaviour on mock SERPs. The fixed-response data showed that the ‘brand name was familiar’ was the most influential factor overall, particularly among older consumers (67.4%). Meanwhile, ‘it was ranked highest’ was notably more important to middle-aged consumers (64.3%). However, the relevance of the description played a secondary role across all groups. Furthermore, qualitative analysis of free-text responses in the ‘other’ category highlighted themes of trust in reputable websites and the value of detailed product information. Together, these findings highlight that both visual cues and familiarity significantly contribute to consumer decisions on search engine results, supporting the concept of position bias and its impact on user behaviour.

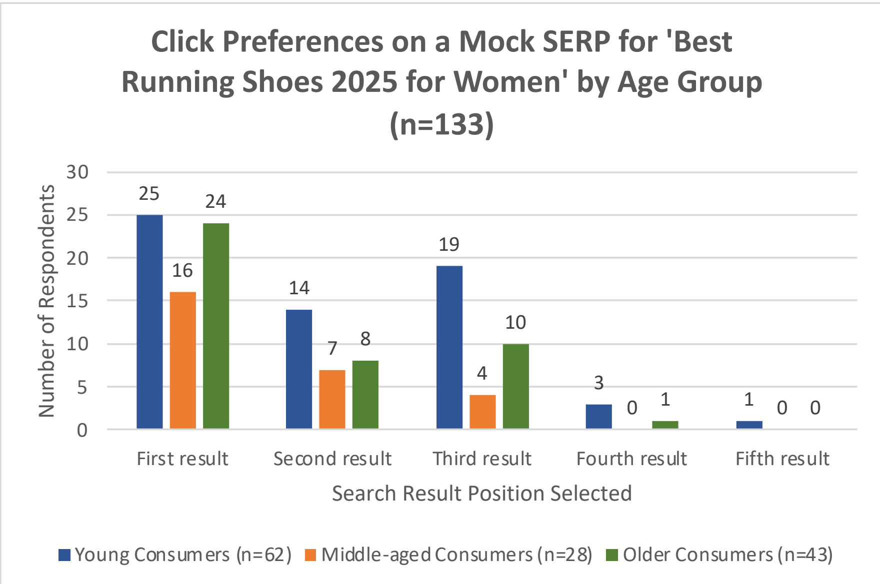

Figure 13. Click Preferences on a Mock SERP for 'Best Running Shoes 2025 for Women' by Age Group (n=133)

Figure 13 shows respondents’ choices when presented with another mock SERP for “best running shoes 2025 for women”, where the second result was a visual product listing ad (PLA). Across all age groups, the first result remained the most clicked option – 40.3% of younger consumers, 59.3% of middle-aged consumers, and 55.8% of older consumers selected the first result. The PLA result attracted more younger users (22.6%) compared to older users (18.6%). This finding suggests that while PLAs catch attention, they do not consistently outperform the top organic listing, particularly among older users who tend to favour the first traditional result.

When respondents were followed up with a question asking respondents to select up to two reasons influencing their decision, the most commonly selected option was ‘the brand name was familiar’ with 46.8% of younger consumers, 28.6% of middle-aged consumers, and 55.8% of older consumers. The responses revealed notable differences in the factors influencing behaviour across generations. In contrast, ‘higher ranking position’ was most prominent among middle-aged consumers (53.6%), while being less influential among the younger (16.1%) and older respondents (39.5%). The ‘other’ category provided further qualitative insight into additional factors such as price visibility and the perceived reliability of the website. These findings suggest that while all age groups consider several factors when clicking on a search result, middle-aged consumers appear to place greater trust in the ranking order, whereas brand familiarity is particularly influential among both the youngest and oldest consumers.

In the next mock SERP questions, respondents were presented with a manipulated mock SERP for ‘Best Running Shoes 2024 for women’ that included a result (option one) derived from an unknown brand, while the remaining results corresponded to well-known brands. The results (see Figure 14) reveal generational differences in click behaviour.

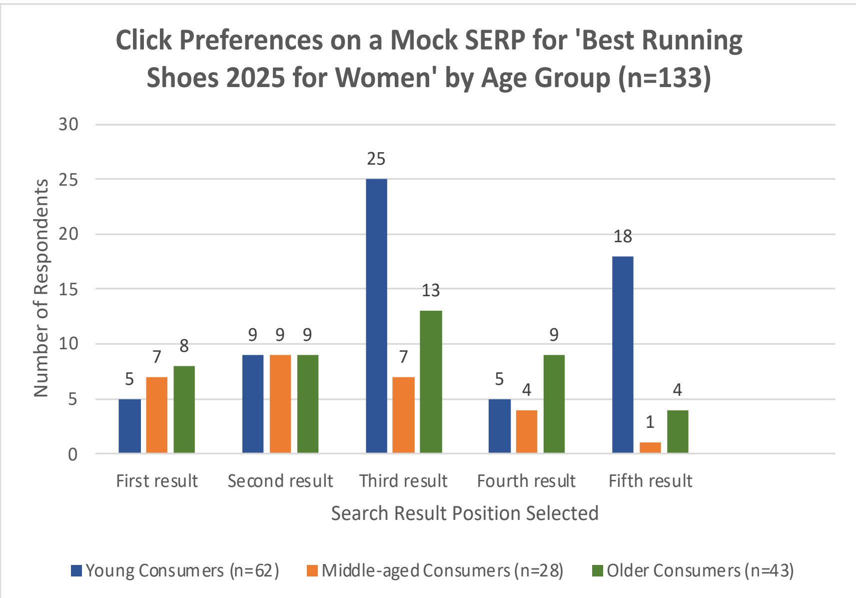

Figure 14. Click Preferences on a Mock SERP for 'Best Running Shoes 2025 for Women' by Age Group (n=133)

Overall, 45 out of 133 respondents (33.8%) selected the third result as the most likely click, as seen in Figure 14. When examined through age group, younger consumers showed the highest preference for the third result, with 40.3% of them choosing it. Middle-aged consumers demonstrated a different pattern: 25% selected the first result, while 32.1% opted for the second, and only 25% selected the third result. Among older consumers, 30.3% selected the third result, with 18.6% choosing the first and 20.9% selecting the second.

These findings suggest that overall, well-known brands have a stronger appeal, particularly among younger respondents who appear to avoid clicking on the unknown brand at the top of the page. Middle-aged consumers, however, seem more influenced by the ranking order, even when the top result features an unknown brand, while older consumers display a more distributed clicking pattern across the results. This analysis highlights the role of brand recognition in shaping click behaviour and supports the investigation of position bias in search engine result preferences.

Among the respondents, the most frequently cited reason for clicking on a search result was that the brand name was familiar, with 83.9% of younger consumers, 64.3% of middle-aged consumers, and 76.7% of older consumers selecting this option. The ranking position of the search result influenced 35.7% of middle-aged and 27.9% of older consumers; however, only 11.3% of the younger consumers. The relevance of description in the search result was chosen by 19.4% of younger, 7.1% of middle-aged, and 22.3% of older respondents. Through the ‘other’ option, highlighted factors like retail reputation and price visibility. Overall, these findings suggest that brand familiarity is the dominant factor influencing click decision, with middle-aged consumers exhibiting a greater reliance on the ranking position compared to their younger and older counterparts.

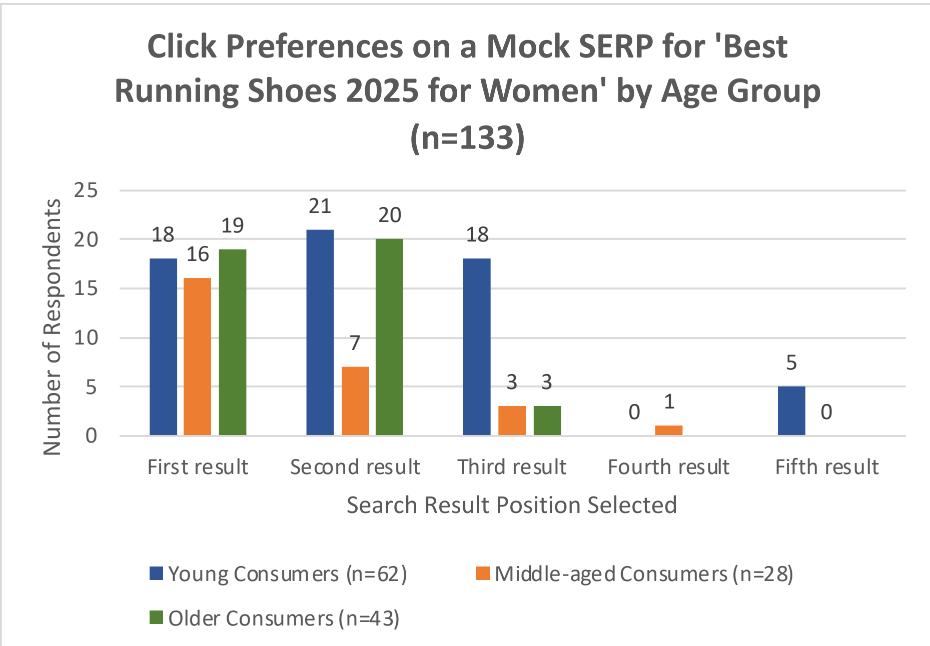

Figure 15. Click Preferences on a Mock SERP for 'Best Running Shoes 2025 for Women' by Age Group (n=133)’

To further analyse the click behaviour of users, the respondents were presented with the last mock SERP that simulates what the search engine would normally show (see Figure 15). Younger consumers were more evenly split across the top three results, with 33.9% of them selecting the second and 29.0% each for the first and third results. Middle-aged respondents favoured the first result (59.3%), while older consumers leaned toward the second (47.6%), followed by the first (45.2%). The last three results received very little attention from the middle-aged and older consumer groups. This suggests that top-ranking results remain influential, but younger users distribute their attention more broadly across the visible options.

4.6 Summary of Key Findings

The survey confirms that age shapes both the mechanics of search behaviour and the degree of position bias in predictable ways. Across all 133 respondents, Google remained the overwhelmingly dominant platform for retail searches. Younger consumers report the highest frequency of daily and weekly searches, the greatest awareness of ranking factors (M = 4.1, CES = 74.2%), and the strongest ability to distinguish paid ads from organic results (M = 3.8, CES = 61.3%). Middle-aged consumers, slightly less digitally skilled (awareness M = 3.0, CES = 32.2%), demonstrated the highest trust in top-ranked results (M = 2.9, CES = 25.1%) and the strongest tendency to click the very first link in both real and mock SERPS (over 70% in many scenarios). Older consumers fall between the two on most measures – less frequent in their searches and less confident in ad-recognition (M = 3.3, CES = 32.6%) but more inclined than younger users to combine position and brand cues when clicking.

Statistical analysis further supports these trends in the generations. Following the ANOVA results, the LSD post-hoc test revealed that younger consumers (M = 3.93) demonstrated significantly higher awareness of ranking factors compared to middle-aged (M = 2.96) and older consumers (M = 3.19), with younger consumers more likely to go past the first page of search results (M = 2.29). In contrast, middle-aged consumers were significantly more likely to trust the top-ranked result compared to both younger (M = 2.10) and older consumers (M = 2.60), with trust being highest among the middle-aged group (M = 2.90).

When presented with mock SERPs, all generational cohorts overwhelmingly favoured the first three listings, but the strength of that bias varied: middle-aged respondents were most likely to click the very first result, younger respondents distributed clicks more evenly among positions 1-3, and older users split their choices between positions 1 and 2. Behind these click patterns lies a clear ranking of click motivations: brand familiarity was the single most cited reason, followed by ranking position (especially among middle-aged and older consumers), with description relevance playing a more additional role.

In combination, these findings illustrate a complex interplay between position bias, brand bias, and generational digital fluency. Younger consumers, though most aware of possible manipulations, still exhibit position bias, albeit more distributed across top results. Middle-aged consumers trust the algorithm's ordering more unreservedly, while older consumers blend trust in position with strong reliance on brand recognition. Understanding these differences is critical for marketers to optimise visibility and promote their webpages on online search results to their ideal consumers.

5 Conclusion

5.1 Discussion

This thesis set out to examine how position bias in search engine rankings influences consumer behaviour across generational cohorts. Overall, the findings confirm that while position bias is prevalent, its strength and manifestation vary by age. Younger consumers, despite having the highest digital literacy and greatest scepticism, will still direct a majority of clicks to the top three listings, although more evenly across those positions than the other cohorts. Middle-aged users demonstrate the strongest trust in the very top result, clicking first almost without thinking, whereas older consumers connect position cues with brand familiarity when choosing. Across all groups, brand recognition was shown to be the single most powerful driver of clicks, often outweighing even ranking position or description relevance.

These results have important implications for digital marketing strategies, particularly in SEO and SEM. Marketers should focus on optimising their positions, particularly for middle-aged consumers, who tend to place the most trust in top-ranked results, ensuring their content ranks highly on search engines. Younger consumers, while more aware of manipulations in search rankings, still exhibit position bias; therefore, brand recognition should be a key part of their search experience to overcome scepticism. Older consumers may require a blend of these, both position and brand cues, so strategies aimed at integrating these elements could be more effective.

These results can be generalised, with appropriate caution, to digitally active populations of similar demographics. However, several limitations must be noted. First, the reliance on a self-reported online survey can introduce potential self-selection bias and may over-represent those already comfortable with digital tools. Second, the sample sizes for each cohort, while sufficient to see any large effects, limit the ability to explore more detailed age brackets or cross-cultural differences. Potential self-selection bias may over-represent those already comfortable with digital tools. Third, mock SERP scenarios, though realistic, will not replicate the situation of live search context, which includes dynamic personalisation and real-time advertising.

5.2 Recommendations for Future Research

Based on the findings, future studies should delve deeper into the psychological side of position bias. Particularly, research could combine a mixed-method user study to explore not only what people click, but how they rationalise this choice in their own words and over time. For an even more in-depth study, partnering with a search platform or simulating one in the laboratory with different variations to measure actual click behaviour and perceived trust in a controlled environment.

Moreover, comparative research across different geographical regions and less dominant search platforms (e.g., Baidu, Yandex) would help assess the generality of these generational patterns. This could also explore whether there are cultural or market-specific factors that alter generational patterns of trust and click behaviour.

Additionally, exploring the impact of real-time algorithms and personalisation would provide further insights into how these factors influence consumer decision-making and behaviour. Research into this would be more accurate to reflect on consumer behaviour in real-life situations, rather than manipulated laboratory environments.

5.3 Reflection on the Thesis Process

Upon reflection on the thesis process, combining quantitative survey data with qualitative mock SERP scenarios proved effective in highlighting broad trends and nuances in click motivations. However, I do recognise that incorporating qualitative interviews with digital marketing professionals or search engine experts could have enriched the analysis, offered a more insider perspective on the algorithmic design, and real-world SEO practices. Additionally, extending the data collection window could have allowed for a larger, more diverse respondent pool and could accommodate temporal variations in search behaviour.

Conducting this thesis has been an intensive learning journey that extended far beyond the topic of position bias. This has sharpened my skills in research design – from crafting and recrafting clear questions, piloting surveys, and defining key measures for trust and bias. Analysing further enhanced my quantitative skillset, from running ANOVAs and interpreting results. Creating mock SERP scenarios fostered a mixed-methods mindset, connecting experiment design with qualitative insights. I gained valuable project-management experience, from maintaining timelines and conducting analysis, while learning to critically reflect on my assumptions and ensure the integrity of my findings.

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Appendices

Appendix 1. Survey Questions

1. By continuing, you confirm that you have read and understood the information

about this study. Your participation is voluntary, and your responses will remain

anonymous. You may exit the survey at any time.

- Yes, I agree to participate.
- No, I do not agree to participate.

2. Which age group do you belong to?

- <16
- 16-24
- 25-34
- 35-44
- 45-54
- 55-69

3. Which search engine do you use most frequently for product or retail searches?

- Google
- Bing
- DuckDuckGo
- Ecosia
- Other (please specify):

4. How often do you use search engines to find information on products or retail categories? *

- Daily
- A few times a week
- A few times a month
- Rarely
- Never

5. When you search for products online (e.g., "best running shoes"), how often do you click on one of the top three search results? *

- Always
- Often
- Sometimes

- Rarely
- Never

6. How often do you go past the first page of search results when looking for products? *
- Always
- Often
- Sometimes
- Rarely
- Never

7. Do you pay attention to whether a search result is a paid advertisement before clicking on it? *
- Yes, I always check.
- Sometimes, but it doesn't affect my choice.
- No, I don't really notice or care.

8. On a scale of 1-5, how much do you trust that the top search result is the best option available?*
- Not at all 1 2 3 4 5 Completely

9. Do you believe that search engine results are unbiased? *
- Yes, I believe they show the best results
- No, I think they are influenced by external factors
- Not sure

10. Are you aware that search engines rank results based on multiple factors, such as search engine optimisation, personalisation, and algorithmic biases? *
- Not at all 1 2 3 4 5 Very aware

11. Do you think search engines favor certain types of content over others? *
- Yes, they prioritise well-known brands
- Yes, they prioritise newer content
- No, I believe the rankings are fair
- Not sure

12. When searching for a product, what factors most influence your decision to click on a result? (Select up to 3) *
- Ranking position (e.g., top result)
- Brand recognition
- Star ratings/reviews

- Price information in the search snippet
- Website (e.g., well-known retailers vs. unknown sites)
- Other (please specify): ___________

13. Do you compare multiple search results before making a purchase decision? *

- Always
- Often
- Sometimes
- Rarely
- Never

14. Which age group do you think relies the most on search engines when shopping online? (Select up to 2) *

- <16
- 16-24
- 25-34
- 35-44
- 45-54
- 55-69

15. Looking at the following search results for "Best Running Shoes 2025 for women" which result would you be most likely to click first? *

- First result
- Second result
- Third result
- Fourth result
- Fifth result
- I would scroll further

16. Why did you choose that result? (Select up to 2) *

- It was ranked highest
- The brand name was familiar
- The description seemed relevant
- Other (Please specify):

17. Are you able to recognise paid ads from organic results?

- Cannot recognise 1 2 3 4 5 Easily recognise

18. Looking at the following search results for "Best Running Shoes 2025 for women" which result would you be most likely to click first?

- First result
- Second result
- Third result
- Fourth result
- Fifth result

19. Why did you choose that result? (Select up to 2) *

- Higher ranking position
- The brand name was familiar
- The description seemed relevant
- Other (Please specify):

20. Looking at the following search results for "Best Running Shoes 2025 for women" which result would you be most likely to click first?

- First result
- Second result
- Third result
- Fourth result
- Fifth result

21. Why did you choose that result? (Select up to 2) *

- Higher ranking position
- The brand name was familiar
- The description seemed relevant
- Other (Please specify):

22. Would you trust the top result more than a well-known brand further down the list? *

- Strongly disagree 1 2 3 4 5 Strongly agree

23. Looking at the following search results for "Best Running Shoes 2025 for women" which result would you be most likely to click first?

- First result
- Second result
- Third result
- Fourth result

- Fifth result

24. Why did you choose that result? (Select up to 2)
    - Higher ranking position
    - The brand name was familiar
    - The description seemed relevant
    - Other (Please specify):

25. Does the ranking position of a product influence how trustworthy you find it?
    - Yes, I trust higher-ranked results more
    - No, I evaluate results based on other factors
    - Not sure

26. Do you have any other thoughts on how search engine rankings influence your shopping behaviour?

27. Have you ever had an experience where search engine rankings led you to a bad or misleading purchase decision?

28. Do you think younger and older generations trust search engine results differently? Why or why not?