# The Rise of AI-powered Search Engines: Implications for Online Search Behavior and Search Advertising

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**Abstract**

The emergence of AI-powered search engines (AIPSEs) present enormous opportunities and challenges for the future of research on search engine behavior and advertising alike. To address these opportunities and challenges, a multimethod study (survey and online observation) was conducted examining relationships surrounding perceptions of different technological affordances offered by AIPSEs and traditional search engines (TSEs), motivations for using each type of SE, behavioral intentions to use each in the future, and actual use behavior. Survey results show that participants perceive the technological affordances of AIPSEs and TSEs to be distinct in several facets, finding AIPSEs to be more cool, social, and responsive while finding that TSEs provide more variety and are easier to navigate. Online search observation results showed heavier reliance on TSEs than AIPSEs, more elaborative keyword use on AIPSEs, and heightened use of AIPSEs in advice-seeking circumstances, among other findings. These results offer both theoretical and practical implications.

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# CHAPTER 1. INTRODUCTION AND BACKGROUND

Over the past 25 years, we have come to rely on search engines (SEs) for everyday tasks, and in turn, our digital media use, information-seeking, and shopping behaviors have evolved. This reliance has gone hand-in-hand with the changing form and function of SEs over this period, with SE providers (e.g., Google, Bing, Yahoo) developing and designing software to make search tasks more streamlined for consumers. Changes to the way in which SEs look and work can be attributed to several factors, including – but not limited to – algorithmic developments (Diakopoulos, 2014; Shahzad et al., 2020; Ziakis et al., 2019), years of user experience (UX) research (Kalbach, 2007; Marcos et al., 2015; Oliveira & Teixeira Lopes, 2023), and competition between different SE providers (Mukhopadhyay et al., 2004; Stucke & Ezrachi, 2016), with each provider vying for higher proportions of consumer usage through innovative offerings.

For example, despite hiding many of their inner workings from public view in proprietary 'black boxes' (Finn, 2019), algorithmic developments have allowed for search engine optimization (SEO) tactics to become increasingly useful through improvements to the way in which relevant content is served to consumers, such as the introduction of Universal Search, the prioritization of high-quality links through programs like Google Panda and Google Penguin, and the Mobile-First wave (Shahzad et al., 2020). What's more, the implementation of software such as knowledge graph technology – a network-like system that allows for the linkage of related concepts and the consolidation of information into succinct paragraphs (Krötzsch & Weikum, 2016) – further altered the traditional link-only layout of the search engine result page (SERP) with multimedia options in 2012, granting users the ability to gather basic information at

a glance while still navigating throughout the SERP. These aforementioned software implementations have allowed SEs to account for the variety of ways in which search tools are used to meet consumer needs, altering the kind of content shown and the way it appears.

While there are a plethora of factors that have influenced SE development over the years, many changes to the form and function of SEs can be attributed to ensuring advertising tactics are as effective as possible, as they account for the lion's share of these SEs' revenues (e.g., 75.9% of Google's 2023 $86.3 Billion Q4 revenue; Alphabet, 2024). In fact, scholars have documented such connections between advertising ventures and changes to SE design (Diaz, 2008; Lewandowski, 2017), discussing the economic implications of placing content at or near the top of SERPs, suggesting that these platforms have a vested interest in changing design aspects to ensure advertising content is engaged with. This creates a precarious relationship between the SEs' goal of providing users with the most relevant content and meeting their bottom line, pushing potentially more relevant content farther down the SERP. With research showing that the rank in which a posting appears can be consequential in terms of performance – including traffic level and number of conversions garnered (Brooks, 2004a; Brooks 2004b) – acknowledging the interconnected nature between SE function, design, and advertising profits is imperative when it comes to understanding how SEs have evolved to their present form, and how they currently serve users content.

These changes in design to SEs have occurred gradually over the last quarter century, many of which we have become accustomed to as consumers and have shaped our view of how and when to use SEs for our given needs; however, within the last year, more drastic changes have occurred. Namely, the rollout of generative artificial intelligence (AI) platforms to the

general public – and more specifically generative AI-Powered Search Engines (AIPSEs; i.e., Google Gemini, Bing Copilot, Perplexity.ai, etc.) – have further altered the search space, allowing consumers to search internet-hosted information in an entirely different manner than previously offered. Just over a year since the public rollout of ChatGPT (November 30th; Marr, 2023) and announcements for Bing Copilot / Google Bard (February 7th; Ortiz, 2024), vast adoption of generative AI technology has been seen among masses of groups, including U.S. Millennials / Gen Z populations (Swartz & Kohner, 2023), and those in various industries (Chui et al., 2023; Thormundsson, 2023). Along with their adoption rate, the pace at which these technologies have changed within this period has been dramatic, with Google Bard changing its name to Google Gemini, upgrading its model capabilities and functional affordances (e.g., adding buttons to double check information accuracy, integrations with programming software through Google Colab; Google, n.d.). These platforms are predicted to fundamentally transform not only how consumers search and find information, but also the business of search advertising, which takes the largest share of digital advertising expenditures (Huh, Nelson & Russell, 2023). Yet, much is still unknown about how consumers have utilized these technologies in this ramp-up period – namely how they use them to satiate their needs and how this may differ compared to the ways traditional search engines (TSEs) are used to satisfy gratifications sought – calling into question what impact their use and adoption may be having on the search environment.

As we move toward a search environment in which an increasing number of individuals may be relying on both TSEs and AIPSEs to gather information about products they are interested in, questions they have, or to seek advice, it is important to investigate if our current understanding of individuals' search behavior will apply to AIPSEs, underscoring the

implications reliance on AIPSEs may have on a wide range of sectors of our society, along with related emerging problems such as misinformation, disinformation, widening digital divide, media users' AI-literacy, etc. Key to this avenue of research is the potential that individuals' perceptions about these technologies, and behaviors on them, may differ between TSEs and AIPSEs due to differences in function and design. Given the dominance of Google over the search engine market share – and by proxy over the search engine marketing (SEM) space where advertisers pay to present content to consumers – for almost the entirety of their existence, the addition of AIPSE platforms may impinge on this market share and pose implications for the effectiveness and reach of SEM campaigns.

**Research Purpose**

With these potential differences and shifts in reliance in mind, the goal of this research is to investigate differences in individuals' perceptions about the affordances of TSE and AIPSE, how motivation to use each type of SE may differ, and how each of these differences may affect behaviors on these SEs, subsequently addressing the implications these behavior differences may have on the efficacy of sponsored advertising on AIPSEs.

As the main theoretical frameworks, both the Theory of Interactive Media Effects (TIME; Sundar et al., 2015) and uses and gratifications (Katz et al., 1973) are applied. Specifically, TIME is used to explain why users may perceive and interact with AIPSEs' functions and content in a different way than TSEs due to differences in affordances offered by each technology. Uses and gratifications is employed to showcase how search motivation may also alter the way in which consumers employ SEs to meet their needs, namely how they affect user action on TSEs vs AIPSEs (clicking and query behavior) and the proportion in which they

choose to use them. It should be noted that we do not attempt to connect motivations to perceptions or vice versa while assessing behavioral intention or measured behavior; rather, we use the affordance perceptions and motivation as parallel influencing factors, examining the ways in which behavioral intention or measured behavior may be influenced by these factors.

To accomplish these goals, a multimethod study is conducted. First, an exploratory survey is administered to investigate whether there are differences in consumers' perceptions about TSEs and AIPSEs due to the different affordances each offers to users. Specifically, this survey examines consumers' (1) perceptions about TSEs and AIPSEs, with a particular focus on perceived coolness, social presence, responsiveness, variety, and ease of use; (2) comparative likelihood of using TSEs/AIPSEs in the future; and (3) awareness of hallucination on AIPSEs. To build off of the findings from this exploratory survey, this study also employs an online search behavior observation research method, using a web interface and Google Chrome extension through which participants' search data are collected – allowing the researchers to see their search queries/prompts, results, and choices on TSE and AIPSE platforms (i.e., clicking behavior) in an unobtrusive manner compared to self-report measures. In addition, we develop a computational model to categorize the motivation of each search conducted. This portion of the study serves a critical role for furthering our understanding of consumers' use of generative AI platforms that is currently understudied.

In combination, the survey and online observation data collection methods allow this research to investigate how consumers' perceptions about and motivation to use these tools may translate to behavior when using them, and how these trends may subsequently affect traditional SEM tactics. Specifically, by comparing differences between affordance perceptions, and

differences in motivation to use each type of search engine, TSEs and AIPSEs, this research contributes to the existing literature that uses TIME and uses and gratifications in relation to emerging technologies and how affordance perceptions and use motivation can contribute to behavior when users interact with them. In a practical sense, this research contributes to the subfield of SEM by exploring aspects that are key to the way in which search advertising campaigns are placed, such as keyword formulation and clicking behavior. By contributing to these theoretical and practical domains, this study outlines new avenues for research at the intersection of human-computer interaction, media psychology, marketing communication, and artificial intelligence.

**Thesis Chapters and Organization**

I arrange this thesis into six chapters. To follow the present introduction and background chapter, Chapter 2 presents the theoretical frameworks that this study relies on; namely TIME and uses and gratifications theory, underscoring the affordances of interactive media used in this study and the ways in which individuals choose to employ said media to meet their needs by reviewing relevant research, subsequently offering an account of specific SE affordances and associating them to the tenets of TIME and discussing findings from related studies. Chapter 3 discusses the hypotheses and research questions that are developed based on the literature review in Chapter 2. Chapter 4 then describes the research methods, samples, and measurement instruments. This is followed by Chapter 5, which presents data analysis approaches and results. Finally, Chapter 6 presents key findings, discusses their implications, and concludes with a section on limitations and avenues for future research in the area.

# CHAPTER 2: LITERATURE REVIEW

This research aims to understand how and why changes in SE function / presentation may have vast repercussions on the field of SEM. In doing so, TIME is used to explain why users may interact with AIPSEs functions / content in a different way than TSEs due to differences in affordances offered by the two types of SEs. Additionally, uses and gratifications theory is utilized to account for the ways in which search behavior may vary when one's motivation to use a SE is taken into account, connecting these motivational aspects to the affordances offered by each SE.

## 2-1. Theory of Interactive Media Effects (TIME)

The Theory of Interactive Media Effects (TIME; Sundar et al., 2015) underscores how advancements in digital communication technology – and more explicitly the interactive nature of digital media – allow for greater autonomy in media consumption than previous traditional media options, demonstrating how the form and function digital media take on allow for differential media experiences. The authors suggest that TIME's underlying argument takes Marshall McLuhan's (1964) sentiment of "the medium is the message" one step further, in that the medium still creates the context in which someone understands and interacts with the message being conveyed, but in this case the medium can be altered to the preference of the receiver of a message. The interactivity aspect of TIME is critical to understand in this context, as the benefit of digital media to a consumer is a product of how one chooses to use it, where some individuals may only use a fraction of the capabilities available to them (Sundar et al., 2017). According to TIME, the potential capabilities of digital media are expected to affect user behavior in two distinct ways: (1) through the actions users have available to them and their

sense of agency over those actions on media interfaces – called the action route; and (2) through the cues that are brought forward in the user's mind as they acknowledge the presence of certain interface features – called the cue route (Sundar et al., 2015).

The interface features available in interactive media technology are referred to as "affordances," which are "action possibilities suggested by visual stimuli in [the] environment" (Gibson, 1977; cited in Sundar et al., 2015, p. 50); or the potential interactive avenues users have available to them within online spaces (i.e., ability to navigate, click, manipulate aspects of the environment). In certain corners of research on affordances scholars have attempted to distinguish affordances from the mere features of media, in that media features exist without consumer perception of or action with that feature (e.g., algorithmic distribution of content on social media), whereas affordances exist at the intersection of platform developer's intentions for a feature and users' perceptions about and actions in response to those features (Zhou, 2021). This qualification allows scholars investigating affordances to better convey the reciprocal relationship between platform and consumer as they traverse these interactive media.

According to the Modality, Agency, Interactivity, and Navigability (MAIN) model, the predecessor to TIME, affordances of interactive media can take on four categories that account for variability in how users' perceptions can be shaped by the cues within a media interface. These categories include: (1) the mode of presentation the interface uses, called *modality*; (2) reference to how media on the interface was created or who it was created by, called *agency*; (3) the ability for one to engage with the interface through responsive functions of the interface, called *interactivity*; and (4) the ability to traverse throughout the interface to explore the potential action offerings, called *navigability* (Sundar, 2008).

### 2-1-1. TIME Research on Affordance Perceptions and Media Use Behaviors

TIME and MAIN have traditionally been used by scholars to evaluate the relationship between perceptions and resultant actions on interactive media interfaces, ranging from behavioral intentions (e.g., intention to use or past use) to actual behavior (i.e., clicking, scrolling, zooming, etc.). Much of this work has been dedicated to understanding and categorizing the varying ways in which technological affordances can be related to particular cognitive states and behavior (Sundar et al., 2015), creating typologies of affordances that can be applied widely to emerging technology (see Sundar & Limperos (2013) for example measures).

In terms of TIME's application to advertising-related outcomes, Sundar et al. (2017) cover a host of use cases in which the theory proves useful in explaining consumers' reaction to and behavioral use of media that disseminate advertising messages. These applications include the use of emerging technologies such as virtual / augmented reality (VR / AR; Lee, Xu & Porterfield, 2021; Sun et al., 2024) and AI chatbots (Ischen et al., 2020; Sun, Chen & Sundar, 2024), which allow consumers to interact with branded content in entirely different ways than before, affecting their perceptions, behavioral intentions, and actions. TIME is adopted in the current study to explore perception differences between TSE and AIPSE software capabilities and layout, highlighting how users may interact with the affordances of each in different ways. In particular, this study focuses on the following five heuristic perceptions: perceived coolness, perceived social presence, perceived responsiveness, perceived variety/browsing, and perceived ease of use.

Perceived *coolness* refers to perceptions about the ingenuity of a medium and its appeal (Wang & Sundar, 2018). Prior research has examined the perceived coolness heuristic in the

context of new media technology and suggested that high levels of perceived coolness may lead to favorable evaluations and increased expectations for the technology (Sundar, Tamul & Wu, 2014) as well as more positive attitudes toward the technology, subsequently resulting in heightened acceptance (Kim, Shin & Park, 2015). Considering this perception is particularly useful in the current context, as AIPSEs are likely to be perceived as novel to consumers who are accustomed to traditional search tools, and thus evaluate them favorably.

Next, perceived *social presence* deals with the humanness of the technological entity with which users are communicating (Sundar, 2008). Studies examining the social presence heuristic have found that when presented with more social machines (i.e., machines that exhibit social tendencies through their interactions), users tend to evaluate those machines more positively in several ways, such as stronger loyalty (Sundar, 2004) and an increased sense of trust (Heckman & Wobbrock, 2000), along with finding that users may apply social rules like politeness to their interactions (Reeves & Nass, 1996). As it relates to AIPSEs, this technology is specifically designed to imitate the human language it is trained on when it provides answers in a conversational style and thus would likely generate higher perceived social presence.

The third heuristic of interest – *responsiveness* – refers to how well the technology reacts to a user's input into the system (Wu, 2006). Some studies have shown that the perceived responsiveness of a computer system is important for creating a connection between humans and the computer system (Wu, 2006) along with helping to build the credibility of the system (Sundar, 2008). Particularly in the context of SE usage, the responsiveness heuristic can be connected to how well a given search engine can react to a consumer query by providing links that are in line with their goals (Sundar et al., 2017) encouraging engagement with content that is

presented. Thus, responsiveness serves an important role in connection to behavioral intentions and actual behavior on AIPSEs vs TSEs, as AIPSEs are built specifically to understand human language on a deeper level, and thus may be able to respond to queries in a more accurate, detailed, and specific manner.

With respect to the perceived *variety* heuristic, this heuristic deals with perceptions about a technology's affordance enabling users to look through a range of results or information (Sundar & Limperos, 2013). Studies have discussed how a variety of options is an important factor in interactive media users' evaluations of technology (Sundar, 2008; Sundar & Limperos, 2013). Additionally, the presence of links has been associated with higher levels of perceived variety, which it has been suggested may encourage users to click on hyperlinks presented, browsing through the options they have available to them to find pertinent information (Sundar, 2008). The level of variety in content presented on AIPSEs vs TSEs is quite different, and thus may contribute to differences in this heuristic.

Finally, perceived *ease of use* addresses perceptions about the lack of mental effort needed to traverse an interface (Wang & Sundar, 2018), which comes from the Technology Acceptance Model (TAM; Davis, 1985) but fits into the navigability category of MAIN. It has been shown that perceived ease of use is a fundamental factor in one's intention to adopt new technology (Kim & Sundar, 2014; Lee et al., 2006), and therefore it is important to consider here, especially given the layout and content differences between AIPSEs and TSEs, along with users' comfortability navigating on each.

## 2-2. Uses and Gratifications Theory

The role of search motivation and its potential impact on individuals' behavior on SEs is justified and explained based on the uses and gratifications (Katz et al., 1973) perspective. The uses and gratifications approach suggests that when individuals choose to use a particular media, they are aware of their motivations and how those motivations align with the abilities of a given media (Ruggiero, 2000), selecting media based on its level of fit. Shade et al.'s (2015) study helps to solidify this connection between individuals' motivations and media selection, showcasing the power of needs (e.g., entertainment, escape, enlightenment) in driving users from one media to another when the former cannot satiate their motivations. This perspective diverges from the traditional media effects research that saw audiences as passive, instead positing that individuals are mindful when choosing to use a certain type of media (Knobloch-Westerwick et al., 2019). Within the last two decades uses and gratifications theory has been widely utilized in the fields of mass communication and advertising, covering domains ranging from internet usage (Stafford et al., 2004; Ko, Cho & Roberts, 2005; García-Jiménez et al., 2012), social media (Chavez et al., 2020; Whiting & Williams, 2013), smart home / AI assistant devices (Lee & Cho, 2020; Xie et al., 2023), and more. Studies in these domains have also utilized uses and gratifications in a comparative sense, assessing the strengths and weaknesses of two or more media in relation to one another (e.g., Gan, 2018; Payne et al., 2003; Quan-Haase & Young, 2010) or how different demographic groups may find a particular media more useful than another based on specific gratifications (e.g., Buf & Ștefăniță, 2020; Deng, Vargas-Bianchi & Mensa, 2023). Both avenues of research provide empirical justification for how motivation can influence behavior on interactive media, and thus allow this study to make similar connections.

### 2-2-1. Uses and Gratifications and Media Use Behavior

Studies employing uses and gratifications or other needs/motivation frameworks for understanding web use have set out to document dimensions of internet use motivations (e.g., information, social interaction, entertainment, pass time, etc.) by understanding how they serve particular gratifications or meet specific needs (e.g., Ko, 2000; Lev-On, 2017; Stafford et al., 2004), in many cases connecting these dimensions to behavioral intention or actual behavior.

Thongmak's (2021) study is a prime example of this subset of research, with the author discussing the many ways in which the internet can gratify one's needs, but focusing on five main gratification constructs with a Southeast Asian sample – passing time, information seeking, entertainment, anti-traditional media sentiment, and internet ambiance – subsequently connecting them to one's search intention, search behavior, and search performance. This study found that the information-seeking and internet ambiance gratifications were significantly positively related to intentions to use the internet, and furthermore found that intentions to seek out information were significantly positively related to search behavior (i.e., how often participants actually used the internet for certain purposes) and their performance while searching (i.e., their level of success in finding the information they were searching for).

More targeted studies have investigated how the motivation to use the internet is related to advertising outcomes, such as attitudes toward content, behavioral intentions, clicking, and query behavior. One such study by Ko, Cho, and Roberts (2005) used confirmatory factor analysis to determine how certain motivational dimensions are related to particular uses of the internet, connecting these uses to behavioral/purchase intentions and actual behavior. Findings from this study indicate that informational motivations were significantly linked to human-to-

message interaction content (i.e., engagement with interactive information on the website) and that social motivations were significantly linked to human-to-human interaction content (i.e., engagement with comments/feedback, surveys, chatrooms, etc.), later finding that these motivations were significantly related to time spent on the internet, increased attitude toward the webpage, and purchase intention. The authors suggest that these findings have implications for the way in which marketers can tailor their content to an audience who may come to their site with a certain motivation, making this content more appealing and in line with each motivational state (Ko, Cho & Roberts, 2005).

Another prominent way in which web search motivation has been conceptualized in prior studies is by examining individuals' queries, dividing them into groups that indicate the motivation of a given search, subsequently tying these motivations to behavior. For example, some scholars have attempted to document how use of the internet can vary by the specificity of the motivation to use it (Hafernik & Jansen, 2013), examining actual queries to determine the motivation. Phan et al. (2007) conducted a set of experiments to classify the degree of information need that one has when searching (i.e., whether a query's need is very broad or very narrow). After categorizing these queries, results were then compared to the number of keywords used in the query, finding that as information need narrows (i.e., specific information is needed) the amount of keywords used increases, indicating that for certain motivational states more elaborative keyword formulation is required and used (Phan et al., 2007), which is consequential for advertisers as they bid on keyword strings for pay-per-click (PPC) advertising campaigns.

Other work categorizing search needs/motivation by investigating queries has divided searches into three groups – informational, navigational, and transactional searches (Broder,

2002). Since this search motivation taxonomy was put forth by Broder (2002), many scholars have employed this categorization scheme to assess web use and behavior (Jansen & Spink, 2009; Terai et al., 2008; Weber & Jaimes, 2011). Notably, Schultz (2020) examined how differing search motivations can affect the kind of information presented and engaged with on SERPs, finding that differing proportions of PPC vs organic options were clicked depending on the associated search need, with important implications for advertisers who pay premiums to have their content displayed (SEM) or optimized to appear (SEO) in search results. In a similar manner, Schultheiß and Lewandowski (2021) employed these motivational categories in an eye-tracking study, finding stark differences between the three motivations and clicking behavior; not only on desktop devices, but mobile devices as well. Indeed, the importance of search needs/motivation in a user's search journey cannot be understated, as their choices of SE, and actions on them, are a product of the needs they have coming into a search and what they believe each search tool will afford them.

As the search environment has evolved, the ways in which individuals use SEs to find information and satiate their needs have changed concurrently with the capabilities and layout of these SEs (Oliveira & Teixeira Lopes, 2023); however, these choices remain a product of the differing technological affordances available on SEs (Lessig, 1999). In the current study, Broder's (2002) original conceptualization of search motivation is altered to fit the more contemporary search environment with both TSEs and AIPSEs, being made up of (1) purchase-related motivations; (2) information-related motivations; and (3) advice-seeking motivations. These categories are useful in investigating the varying manner in which needs can be satisfied by these SEs, helping uncover the ways in which the search environment may change as TSEs

compete for use with AIPSEs. By taking a comparative approach (i.e., assessing the differences in uses and gratifications between two types of interactive technology), uses and gratifications can be employed to understand how the usefulness of each search tool differs based on individual circumstances, where SEs and their content serve to satiate the needs of users in distinct ways depending on the details of those needs. What's more, by categorizing search motivations in this manner, this study is able to examine how motivations may affect whether a user chooses to search on a TSE vs AIPSE, along with actions that are associated with these motivations – like keyword elaboration and clicking behavior – all of which are connected to the effectiveness of search advertising.

## 2-3. Research on Search Engines and Affordances

### 2-3-1. Traditional Search Engines

Search engines are computer programs that enable users to interact with the vast Web by entering search terms through the frontend interface and navigating search results. The backend SE technology constantly gathers and updates website index data and returns relevant website directories that match a search term to the user via the frontend result page interface (Kritzinger & Weideman, 2005). With the current mass reliance on web-mediated search to complete daily tasks considered, designing modern search engines in a manner that allows users to get to pertinent information most efficiently has become particularly important. As a result, TSE providers have developed a host of features that have made search more streamlined, changing the action abilities available to users. This section discusses features that exist in both the backend functionality of TSEs and the frontend presentation and layout, and how they can be conceptualized as affordances.

First, it is important to discuss the inner workings of SEs and how search engine result pages (SERPs) are constructed, being made up of sponsored content options (i.e., pay-per-click (PPC) advertising) and organic result placements, discussing how the recommendation system provides users of TSEs with a plethora of options to choose from. In PPC advertising, advertisers bid for a space at the top of a SERP based on keywords or phrases, and then pay the search engine an agreed-upon amount every time a consumer searches with those keywords/phrases and subsequently clicks on their ad placement (Kapoor, Dwivedi & Piercy, 2016). The order in which these ads appear – or ad rank – depends on how aggressively one bids on certain keywords or phrases, with those placing the highest bid being featured at the top of the paid advertisement section (Jansen & Schuster, 2011). Additionally, the cost of these keywords is a product of search demand, where shorter, commonly searched keyword strings (fat-head strings of 2 or less words) typically cost more and face more competition, whereas more elaborative strings (long-tail strings of 4 or more words) are relatively less expensive, but are harder to target (Kritzinger & Weideman, 2013; Ramaboa & Fish, 2018)

In contrast to paying for one's space on the SERP, search engine optimization (SEO) involves fine-tuning one's website so that it appears higher on a SERP for a given set of keywords or phrases. The act of "fine-tuning" refers to the enhancement of a website through design, html coding, and maintenance, ensuring that certain keywords are linked to the website which allows it to appear highly in the organic results section (Davis, 2006). The SEO fine-tuning helps a TSE's algorithmic software 'crawl' the internet to "gather potentially matching keywords included in the search query and collects the content," eventually presenting the searcher with the most pertinent information in order (Sharma et al., 2019, p. 687). In the context

of this study, both PPC and SEO strategies are important to understand in terms of how these strategies allow for the distribution of content to individuals on TSEs; whereas AIPSEs use markedly different methods to serve content to users, which will be covered further below.

When it comes to frontend functionality aspects of TSEs, the following two aspects are the focus of our discussion: (1) the presence of multiple PPC and organic options to choose from in the "core" of the SERP; and (2) the presence of knowledge graph options.

*Core options:* Many studies have investigated the way in which the affordances of TSEs affect how users gather information – focusing on user experience (UX) in a functionalist sense by examining the role of SERP layout and the presence of software features on choice (e.g., Lawrance et al., 2010; Schnabel et al., 2019). For example, Azzopardi et al. (2018) suggest that the SERP can be divided into four distinct sections, including the header (e.g., search box), footer (e.g., page numbers), right rail (e.g., knowledge graph options) and the core (e.g., URL links) – and find that the arrangement of the core can affect user choice in terms of cost to forage certain material. One of the affordances being considered in the research is the presence of core options in the form of PPC and organic links. The consistent presence of options to interact with and choose from when deciding what information will best suit users' needs in a given context can be seen as a benefit brought to users by TSEs (Schultheiß & Lewandowski, 2021).

*Knowledge graphs:* Over the last decade more complex features have been introduced to the TSE interface – most notably Google's Knowledge Graph in 2012 (Ehrlinger & Wöß, 2016), which allows Google to present users with immediate, synopsized information it deems to be most applicable based on a given query. One example is a knowledge panel interface, which contains summaries of information about places, companies, concepts, etc., taking on various

forms in the left and right-rails, breaking away from the traditional vertical layout of SERPs. Featured snippets are another prominent knowledge graph feature, providing users with a succinct answer, typically in paragraph, list, or table form (Strzelecki & Rutecka, 2020). In many cases these multimedia options do not require users to navigate to clicked-results pages, allowing them to get basic information at a glance while still staying on the SERP. This provides an interesting parallel to how AIPSEs function, and the way in which information is consumed when the content is summarized for the user.

### 2-3-2. AI-Powered Search Engines

In this literature review, it is important to distinguish between research that focuses on Generative AI vs AIPSEs, as they have distinct capabilities, and the focus of this study is on AIPSEs exclusively. The primary difference between the two is that Generative AI, or large language model (LLM) programs like GPT-3.5 (OpenAI, 2023) and PaLM, do not have an internet connectivity (although newer models like GPT-4 and GPT-4o have integrated these features (Agarwal, 2024; Wilkinson, 2024)) and therefore are only able to generate content from the information it has been trained on (or synthesize new information from its own weights), which while extensive is not as easily adaptable. In contrast, AIPSEs (e.g., Google Gemini, Bing Copilot and Perplexity.ai) rely on these LLMs as a base for interpreting and generating responses, which once combined with search engine capabilities are able to generate answers that factor in real-time information from the internet (Pichai, 2023). While both of these types of LLMs are worthwhile to investigate, this study focuses on AIPSEs alone due to their capability to connect to search engines and provide users with real-time search results, like product/service

pricing, reviews, availability, etc., highlighting the potential they have to disrupt the effectiveness of SEM on traditional SEs.

These computational models are trained on extremely large corpora of text data and are intended to produce text that interprets and imitates human language through a process called next token prediction – a branch of Natural Language Processing (NLP) – which analyzes words in text by breaking them down into smaller components called tokens, subsequently producing a textual output as a function of the weight of each of these tokens through Transformer architecture (Ahmed et al., 2023). Compared to the TSEs, AIPSEs take very different shapes and forms in terms of both frontend interface and backend search result generation mechanism. Although there is a plethora of news covering the disruption that AIPSEs have caused in many areas, little research exists on this topic in the communication field. Thus, to conceptualize affordances offered by AIPSEs, this study relies on emerging conceptual or descriptive studies in other disciplines that explore the ways in which generative AI platforms can be leveraged. We categorize the unique affordances of AIPSEs into three aspects: conversational agent, advice generation, and information aggregation and synopsis presentation capacity.

*Conversational Agent*: This technology can take on a social role through its ability to interpret and mimic human language, where the AIPSE understands conversational search queries and presents answers in a way that mirrors how another person may relay them to you (Haleem et al., 2022). This *interpretation* aspect plays into the heightened ability of AIPSEs to recognize user intent and react to the goal of a query in a more accurate manner compared to TSEs, which Haleem et al. (2022) suggest may enhance response quality and user experience as they become more familiar with how to prompt the AIPSE. This ability of AIPSEs to mimic

humans and interpret their goals as a *conversational agent* would likely trigger perceptions of social presence and responsiveness of the technology, and influence users to evaluate them more positively and interact with them politely due to the interpersonal nature of their communication, which researchers have suggested can occur when humans interact with more social machines (Nass & Moon, 2000).

*Advice Generation*: Some studies investigating the future of generative AI in marketing contexts have suggested that these tools can be utilized beyond content creation and conversation, helping to both analyze client and company data, while also inspecting market trends and providing step-by-step plans to capitalize on them (Haleem et al., 2022; Ray, 2023). In essence, this is connected to the generative AI's capacity to generate advice and AIPSEs' ability to provide recommendations in varying circumstances, such as meal plans, travel itineraries, etc. These kinds of responses can be lumped together in a single category called *advice generation*, which is characterized by the technology's features enabling users to rely on AIPSEs for help weighing the pros and cons of alternatives and providing opinions.

*Information Aggregation/Synopsis Presentation Format*: Within AIPSEs' ability to generate content is the capacity for this technology to gather large amounts of information and create succinct summaries of their main points (Haleem et al., 2022), and in some cases provide links to show where it pieced together the answer from (Liu et al., 2023). This ability can be extremely useful in many cases, especially in those where source information may be hard to track down, or in cases where users have limited time or motivation to examine multiple sources to gather needed information themselves. Additionally, these synopses provided in AIPSE results serve to make the layout of this information more digestible than TSEs, taking away much of the

clutter and focusing user attention. Despite the potential positive psychological effects this technological affordance can cause, the information-aggregation/synopsis-generation feature is prone to generating inaccurate or fabricated information, referred to as "hallucination."

*AI Hallucination and Users' AI Literacy:* The AI hallucination process is characterized by information that is presented in a factual manner by the AIPSE, when in reality it is either not wholly backed up by supporting evidence or is entirely fabricated (Mckenna et al., 2023). In light of this issue, some researchers have set out to document these errors and call for developers to fix these issues before wide-scale public rollout of AIPSE products (Zhao et al., 2023). In one such study, researchers from Stanford University conducted an evaluation of the information generated by AIPSEs, finding that only 51.5% of responses generated by AIPSEs were fully supported by their citations, and that only 74.5% of the citations presented fully supported their accompanying statement (Liu et al., 2023). It should be noted that the ramifications of hallucination are not limited to AIPSEs, in that when these incorrect or fabricated answers are spread to clicked-result pages posted on the internet (e.g., posted on blogs), TSE technology, such as Google Knowledge Graph, can end up referencing them, further spreading misinformation. In a recent case, blog sites "https://news.ycombinator.com" and "https://www.emergentmind.com/" posted examples of hallucinations by Generative AI about "African countries that start with k," where the program reported that no countries in Africa begin with "k" (Christopher Ingraham, 2023), which is of course untrue. These pages were then referenced by the Google Knowledge Graph in the form of a featured snippet when individuals search the same "African countries that start with k" query, providing the same factually incorrect answer.

The issue of hallucination is vital to discuss here, as this defect could potentially cause distrust among users about AIPSEs' ability to provide them with accurate information, which could affect their perceptions about the usefulness of these technologies and their intention to adopt them. Conversely, users could be wholly unaware of this issue, and thus unknowingly distribute information to others or en masse on the internet, which has implications for misinformation spread and potential need for AI-focused media literacy initiatives. It is for this reason that this study also investigates the awareness individuals have about this issue, and how they are using AIPSEs vs TSEs when confronted with verifiable information they are wary of.

### 2-3-3. Comparing the Affordances of TSEs and AIPSEs

Through outlining the potential affordances offered by both TSEs and AIPSES, several stark differences in functionality and presentation are apparent. First, the availability of links is quite variable between the two, as TSEs are composed mainly of hyperlinked options, whereas AIPSEs offer less variety in answers and fewer hyperlinked options to find additional information. This reduction in hyperlinked options on AIPSEs is related to the next comparative difference – the way content is presented on two options – where AIPSEs provide succinct synopses in response to queries and TSEs require users to click into result pages to find their answers (albeit in cases where knowledge graph options can answer their question). Given their NLP capabilities, AIPSEs are better able to interpret the meaning of users' queries compared to TSEs in many cases, potentially providing these users with more accurate search results; especially considering the ability of consumers to elucidate their needs through iterative chats in a single session, adding clarifying notes to a query which can be stored throughout these sessions in the AIPSEs context window (Ahmed et al., 2023). This ability of interpretation on AIPSEs

also encompasses the social nature of this technology, where responses are generated in longer form, paragraph responses, mimicking the way in which a consumer may talk to another person. Finally, the novelty of all of these new features on AIPSEs – compared to the homogeneity of features across TSE platforms – may lead consumers to assess these platforms as futuristic and cool compared to search platforms they are used to engaging with. These comparisons are only a few of the many which could be made.

Juxtaposing the action possibilities of TSEs / AIPSEs and the content that they each serve to users, it becomes clear that certain searches may be more appropriate to conduct on one option over the other. It is possible that in cases of information or advice seeking AIPSEs may be an appropriate choice due to its ability to succinctly condense information into digestible text while eliminating much of the effort traditional SEs require to find pertinent information. However, it is also plausible that the presence of a variety of sources on TSEs that can be browsed through will be preferred in instances where information or advice are needed. Additionally, due to the current lack of advertising materials and variety in presented content, along with difficulty conducting purchases through AIPSEs, they may be less useful in comparison to traditional SEs in these contexts. It remains to be determined to what extent searches of a particular motivation will be conducted on each SE, as it is possible that this distribution of searches in a particular motivation could be proportionally equal across SEs, or skewed toward one over another. Examining this sort of distribution will not only provide further context as to how each of these SEs is used comparatively, but will also help us understand what place PPC advertising may have on AIPSEs depending on proportions of purchase-related or advice-seeking searches,

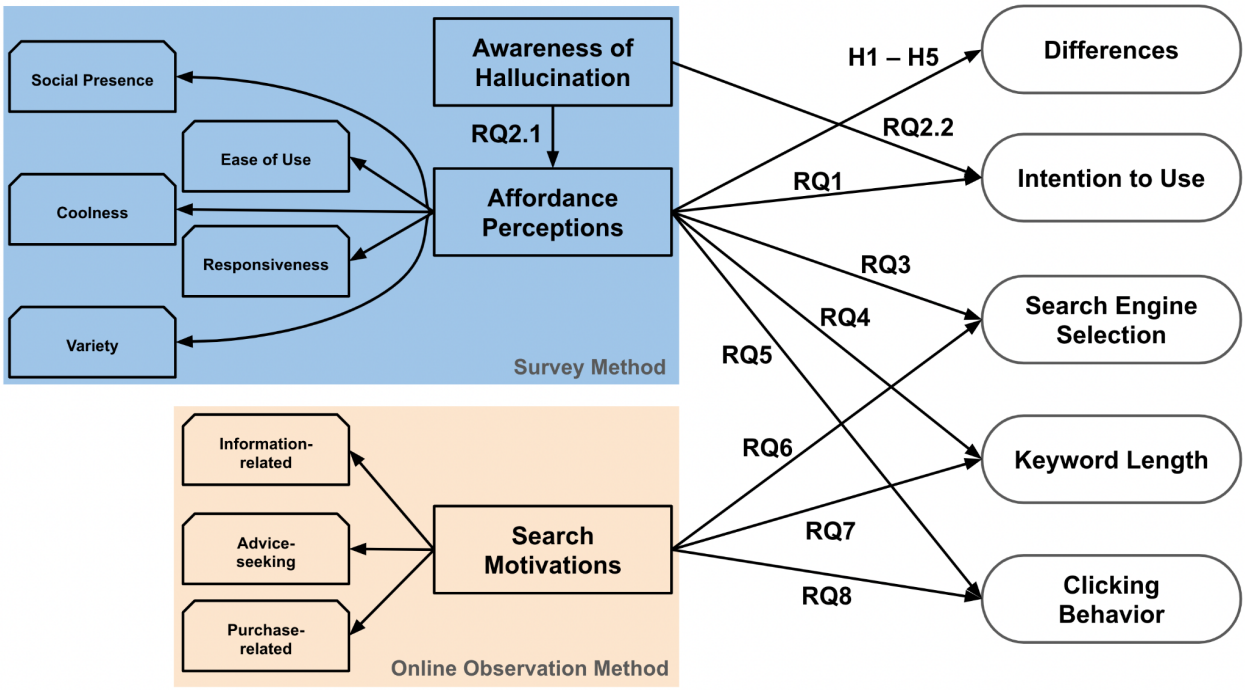
whether users tend to click on the AIPSE links that are provided, and how elaborative their queries are in these states.

# CHAPTER 3: HYPOTHESES AND RESEARCH QUESTIONS

The hypotheses and research questions that follow were developed in connection to two avenues of prior research, including: (1) affordances of TSEs and AIPSEs that are discussed above, based on findings from prior research applying MAIN and TIME to examine relationships between affordances of digital media and users' heuristic perceptions and actions; and (2) in relation to users' distinct motivations when searching on SEs, referencing research that has investigated how search intent is a factor that can affect choice of content to engage with and how to form ones query. These hypotheses and research questions are divided methodologically (see Figure 1 for the study outline). The first set, covering connections between survey response variables, encompasses (1) H1–H5, investigating differences between TSE and AIPSE affordance perceptions; (2) RQ1, examining the relationship between the perception variables and self-reported likelihood of using each SE; and (3) RQ2, investigating connections between AI hallucinations awareness and perceptions / likelihood of using each SE.

With respect to connections between survey responses and online observation data, three research questions are posed (RQ3-RQ5) to consider connections between individuals' affordance perceptions to SE choice, query length, and click choices. Examining relationships that exist in the online observation data alone, three additional RQs are posed (RQ6-RQ8). RQ6 investigates differences in SE selection based on the associated search motivation. RQ7 is concerned with query length, examining whether there are significant differences in query length between searches on each type of SE and investigating if these differences remain when search motivation is accounted for. Finally, RQ8 investigates relationships between search motivation and click behavior between the two types of SEs.

**Figure 1.** Multimethod Study Design




## Hypotheses

Beginning with our hypotheses, H1-H5 focus on the following five perceptions: perceived coolness, perceived social presence, perceived responsiveness, perceived variety, and perceived ease of use. With respect to the perceived coolness heuristic, due to the newness of generative AI and AIPSEs and the amount of media coverage around them and their abilities to streamline search (Haleem et al., 2022; Hu, 2023; Pichai, 2023), it is predicted that individuals would likely find AIPSEs to be original, different, and appealing, and thus perceive them to be more "cool" than TSEs:

**H1:** AIPSEs will likely generate higher perceived coolness compared to TSEs.

Perceived social presence of AIPSEs is connected to the conversation agent and human-like communication affordance of AIPSEs, as discussed earlier. Prior research has suggested that

the way in which AIPSEs relay information can be perceived as human-like (Haleem et al., 2022) and potentially invoke interpersonal communication-like responses, and thus the following prediction is made:

**H2:** AIPSEs will likely generate higher perceived social presence compared to TSEs.

With respect to the third heuristic of interest, perceived responsiveness, the aim is to connect findings from prior research on responsive technologies (Sundar, 2008; Wu, 2006) to the backend capacity of AIPSEs to interpret a user's query goals through next token prediction – which manifests visually for the user through the conversational responses from the system and their ability to clarify their needs based on prior queries. It is predicted that this ability for heightened query interpretation on AIPSEs compared to TSEs would likely provide users with stronger perceptions of responsiveness of AIPSEs to their queries; thus, this study poses the following hypothesis:

**H3:** AIPSEs will likely generate higher perceived responsiveness compared to TSEs.

Turning to the perceived variety heuristic, this research suggests that the presence of choices on an interface may trigger this heuristic by providing consumers with a plethora of hyperlinked options in response to their search, leaving the onus on their end to find the answer they are looking for within this set. The presentation of a variety of options on TSE results would likely lead to higher levels of perceived variety compared to AIPSEs, whose synopses and limited links may leave users wanting. As such, the following hypothesis is proposed:

**H4:** TSEs will likely generate higher perceived variety compared to AIPSEs.

Finally, being that this study is concerned with the potential use of AIPSEs and media users' evaluations of their utility compared to TSEs, using perceived ease of use as a measure is

apt. In light of the fact that AIPSEs present their content in easily digestible, synopsis form – while also at times providing linked sources for users to access – it is possible that users will perceive their ability to navigate throughout and use AIPSE content as easier than that of TSEs, and so the final hypothesis is posed:

**H5:** AIPSEs will likely generate higher perceived ease of use compared to TSEs.

**Research Questions**

In addition to the above hypotheses, two research questions are posed dealing with relationships between the survey response variables. The first (RQ1) investigates the relationship between the five perceptions outlined above and likelihood of choosing AIPSEs over TSEs, as the perceptions that this study hypothesizes may be higher for AIPSEs than TSEs may be positively related to the likelihood of choosing AIPSEs. For example, prior research has examined perceived coolness heuristic in the context of new media technology and suggested that high levels of perceived coolness may lead to favorable evaluations and increased expectations for the technology (Sundar, Tamul & Wu, 2014) and more positive attitudes toward the technology, subsequently resulting in heightened acceptance (Kim, Shin & Park, 2015). Prior research examining the social presence heuristic has also found that when presented with more social machines, users tend to evaluate those machines more positively in several ways, such as stronger loyalty (Sundar, 2004) and an increased sense of trust (Heckman & Wobbrock, 2000). However, prior evidence for the relationship between different heuristic perceptions and the comparative likelihood of choosing new digital media technology vs older technologies is scant, and no research has examined AIPSEs in this manner. Thus, the following research question is posed:

**RQ1:** How are the perceptions about AIPSEs and TSEs related to the likelihood of choosing AIPSEs over TSEs?

This research question will be examined in each of the three aforementioned search motivation contexts. As discussed, search motivation has been shown to be consequential in terms of which media appears useful and gets selected depending on media users' motivations (e.g., García-Jiménez et al., 2012; Ko, Cho & Roberts, 2005; Stafford et al., 2004; Thongmak, 2021). Similarly, it is assumed that search motivation may affect users' intention to use an AIPSE vs a TSE in the future.

Additionally, we pose a research question (RQ2) dealing with the issue of hallucination on AIPSEs, examining how individuals' awareness of hallucination is related to their perceptions of AIPSEs. As we have noted above, AIPSEs in their current form are capable of hallucinating information, which poses vast issues for the spread of misinformation. Thus, we seek to understand to what level individuals are aware of hallucination, and how this affects their perceptions of AIPSEs affordances. We find it important to examine if individuals' awareness about hallucination may go hand-in-hand with their perceptions, as it is possible that one's high levels of awareness may dissuade consumers from adopting these search tools in any fashion. Thus, we pose the following research question:

**RQ2:** How is one's awareness of hallucination on AIPSEs related to (2.1) the perceptions about AIPSE affordances; and (2.2) their likelihood of choosing AIPSEs over TSEs?

Connecting the survey responses to the online observation data collected through our Google Chrome extension, three research questions are put forward. The first, RQ3, investigates the relationship between the five perceptions outlined above and the proportion with which users chose each SE (i.e., out of a user's total searches, how many were on each SE). In regard to the

relationship between perceptions about new media and the proportion one uses that technology, prior studies listed above have examined how each of the five perceptions about interactive media can translate to adoption of the technology or favorable attitudes toward them (e.g., Heckman & Wobbrock, 2000; Kim, Shin & Park, 2015; Kim & Sundar, 2014; Lee et al., 2006; Sundar, 2004; Sundar, 2008; Sundar, Tamul & Wu, 2014; Sundar & Limperos, 2013; Wang & Sundar, 2018; Wu, 2006). Despite this evidence suggesting that high levels of these perceptions can be linked to increased adoption intention, it may be the case that high levels of certain perceptions may be more important than others, or may have no effect on selection in the case of AIPSEs. Hence, it is imperative to assess the connections between perceptions and increased use/adoption of AIPSEs, and thus the following research question is posed:

> **RQ3:** How are the different perceptions about AIPSEs and TSEs related to search engine selection, and which perceptions are most strongly related?

Addressing individuals' average query length, RQ4 investigates the possibility that users' perceptions of AIPSEs' ability to respond to complex prompts with precision will elicit more elaborative queries from users to specify their search needs, as was shown in Phan et al.'s (2007) study investigating specificity and query length. Given that prior evidence surrounding the relationship between these heuristic perceptions and the actual use of a new digital media technology is scant – and that little research has examined AIPSE use generally – the following research question is presented:

> **RQ4:** How are the responsiveness perceptions about AIPSEs and TSEs related to the length of one's queries on TSEs vs AIPSEs?

Finally, RQ5 examines whether one's clicking behavior on these SEs may be tied to users' perceptions about the amount of variety each SEs provides them, as the presence of links

has been shown to trigger this heuristic (Sundar, 2008), and to be able to click one must be presented with links on a given interface. Clicking behaviors may also be tied to the perceptions of responsiveness of each system, as systems that are responsive to one's query would provide links worth clicking on. In line with these assumptions, the next research question is as follows.

> **RQ5:** How are the responsiveness and variety perceptions about AIPSEs and TSEs related to link-clicking behavior on TSEs vs AIPSEs?

Investigating trends within the individual search episodes gathered, three additional research questions (RQ6, RQ7, and RQ8) are posed. These questions are concerned with how one's search intent or underlying motivation in a search may affect which SE is selected, the way in which they form queries on each of them, and what they click on/if they choose to click on anything at all. As mentioned in the literature review, we adapt Broder's (2002) search need taxonomy to three tangential categories, including (1) purchase-related motivations, (2) information-related motivations, and (3) advice-seeking motivations, and suggest this categorization scheme is better aligned with how users' searches may differ between AIPSEs and TSEs.

With respect to RQ6, we examine how search engine selection is affected by consumers' search motivation, where some searches may be better answered on TSEs than AIPSEs and vice versa, depending on the search motivation. Studies employing uses and gratifications have showcased how individuals' media use motivations can affect media selection as a product of that media's fit to their needs, such as Shade et al.'s (2015) study investigating the power of needs (e.g., entertainment, escape, enlightenment) in driving users from one media to another when the former cannot satiate their motivations. Thus, we suggest it is appropriate to investigate

whether certain search needs are satiated more often by one type of SE compared to the other. To answer this, RQ6 is proposed:

**RQ6:** How is the selection of TSEs vs AIPSEs affected by search motivation?

The next research question investigates whether there are significant differences in search keyword length depending on the motivation one searches with while controlling for which type of SE is used. Using the same rationale posed above regarding affordances and query length from Phan et al. (2007), it is likely that perceptions of AIPSE responsiveness may lead to more elaborative searches compared to those conducted on TSEs, as searches that include more detail on AIPSEs will result in more specific answers. Additionally, in line with findings presented in the literature review regarding search need and use behavior, we suggest that considering search motivation is crucial when examining the actions one may take on each SE after they have selected it. As such, we seek to investigate whether different types of queries will demand different levels of specificity (i.e., amount of words used), and suggest that this relationship may be jointly affected by which SE a user chooses to use to satiate their search need. We pose the following research question:

**RQ7:** How is keyword length on TSEs vs AIPSEs affected by search motivation?

Finally, there may be a relationship between search motivation and whether a user clicks on a linked option, along with significantly different clicking behavior between SE types while controlling for motivation (i.e., purchase-related motivations on TSEs vs purchase-related motivations on AIPSEs). In line with findings regarding connections between search need and clicking behavior (e.g., Schultheiß & Lewandowski, 2021; Schultz, 2020), we suggest that

considering motivation is crucial when examining actions one may take on each SE. As such, we pose the following question:

**RQ8:** How is link-clicking behavior on TSEs vs AIPSEs affected by search motivation?

Little to no research has looked at how search motivation can affect comparative SE selection (likely due to search tools being relatively homogeneous until very recently), the way users form queries on SEs, or whether users choose to click on links presented to them on the platform; thus, this group of research questions help to showcase the differences in behavior on AIPSEs and TSEs while also linking them to the underlying motivation an individual is in when making these decisions.

# CHAPTER 4: METHODS

Considering the relative novelty of AIPSE platforms and the current lack of concrete knowledge about how individuals perceive and use them compared to TSEs, we set out to collect both perceptual and behavioral intention data through a survey method, along with online search observation data to examine individuals' actual behavioral engagement with each SE type. We find that in combination, data from these methods provide a more holistic picture compared to one method alone. Below we describe the samples and measurements in each method that allow us to test the hypotheses and answer the research questions posed.

## Survey Method

An online survey was conducted with a purposive sample of 564 participants recruited from Prolific. The sample inclusion criteria were: (1) 18+ years old, (2) living in the U.S., and (3) had used BOTH a TSE and an AIPSE in the last three months. Participants were presented with a consent form approved by the University of Minnesota IRB (STUDY00019923), and by selecting "yes" to this agreement were then sent to the questionnaire. Those who completed the questionnaire received compensation of $2.80 for their time.

### Survey Measurements

The questionnaire measured: (1) affordance perceptions about TSEs and AIPSEs, with a particular focus on perceived coolness, social presence, responsiveness, variety, and ease of use; (2) comparative likelihood of choice between TSEs and AIPSEs; (3) awareness of hallucination on AIPSEs; and (4) demographics including age, gender, race, education level, and employment status. See Appendix A for the full list of measures.

*Perceived coolness* was measured with a five-item 7-point Likert scale adapted from Wang and Sundar (2018), including "___ search engines are on the cutting edge," "It's cool how ___ search engines work." (AIPSE Cronbach's **α** = .913; TSE **α** = .844). *Perceived social presence* was measured with a four-item 7-point Likert scale adapted from Wu (2006), including "After using a ___ search engine, I come away feeling like I had a personal conversation." (AIPSE **α** = .821; TSE **α** = .828). *Perceived responsiveness* was measured with a four-item 7-point Likert scale adapted from Sundar and Limperos (2013) and Wu (2006), including "___ search engines have the ability to respond to my actions on their interface quickly and efficiently." (AIPSE **α** = .848; TSE **α** = .778). *Perceived variety* was measured with a four-item 7-point Likert scale adapted from Sundar and Limperos (2013), including "___ search engines allow me to obtain a wide variety of information." (AIPSE **α** = .842; TSE **α** = .809). *Perceived ease of use* was measured with a three-item 7-point Likert scale adapted from Wang and Sundar (2018), including "Navigating on a ___ search engine does not require a lot of mental effort." (AIPSE **α** = .865; TSE **α** = .807).

The *likelihood of choice* between TSEs and AIPSEs was measured with nine hypothetical search motivation scenarios, including (1) three purchase-related situations, (2) three information-related situations, and (3) three advice-seeking situations. For each search scenario, participants were asked to choose how many times out of 10 they would choose a TSE or an AIPSE in that instance, making each evaluated on an eleven-point scale (i.e., options ranging from 10/10 TSE – 0/10 AIPSE (coded as 0) through 0/10 TSE – 10/10 AIPSE (coded as 10)). It should be noted that these motivational scenarios were not overtly distinguished to the participants in the survey to avoid response bias.

Finally, one item measured individuals' awareness of hallucination on AIPSEs on a 5-point scale, with options including full awareness (5), adequate awareness (4), basic awareness (3), minimal awareness (2), and no awareness (1). This item was measured after the participants were asked about their AIPSE perceptions, as to not influence their scores in any way.

**Online Search Observation Method**

For the online observation data collection, participants were asked at the end of the survey if they would be interested in learning more about a second aspect of the study where they would be asked to search the web as they normally would for 24 hours. This part of the study involved collecting real-time participant search data on a traditional search engine platform (i.e., Google) and on an AIPSE platform (i.e., Google Gemini (Bard when this study was conducted)) for a 24-hour period. To accomplish this, we asked participants to download and install a Google Chrome extension onto their browser and navigate to a simple web interface from our onboarding materials, through which they will be given individual credentials to sign into with. Participants who agreed and participated were paid $1 for logging into the web interface correctly, and $4 for producing usable data within their 24-hour period, no matter how much data was produced. Online observation data was collected with a Google Chrome extension built by a computer science graduate student at the University of Minnesota-Twin Cities. This extension collected the following information, including: (1) what type of search engine was used (AIPSE vs TSE), (2) search queries typed into the SE; (3) results presented to the user on the SE (i.e., links (PPC, organic, and knowledge graph) on TSEs and text response + links on AIPSEs); and (4) results clicked on out of the results presented. See Appendix B for recruitment and onboarding materials.

Of the 564 participants originally recruited for the survey, 388 indicated their willingness to learn more about the online search observation study. Of those 388, 118 agreed to participate by electronically signing a consent form approved by the IRB at the University of Minnesota-Twin Cities (STUDY00019923). Participants were given individual Gmail email addresses to log into Google to ensure their anonymity and data privacy while searching the web, which also served as their credentials to log into our web hub and Google Chrome extension. Of these 118 participants, 39 logged into our web hub correctly and provided us with usable search data. Each participant was given 24 hours to search from the time of their first login and was told to search as they normally would in any other circumstance. These 39 participants produced 623 individual searches (the mean number of searches per participant was 16 (SD = 12.7)).

**Online Search Observation Tools**

To collect participants' search behavior data, we developed an innovative online search observation method using our own Google Chrome extension built in collaboration with computer science researchers (see Figure 2). The *Chrome extension* was created to track users' search engine choice and search behavior logs (keywords, queries, search results, clicks, and window and tab usage) to our local server when specific search events are triggered. The *Backend API* coordinates data flow between the Chrome Extension and the database. Flask, a Python framework, serves as a communication bridge and a gatekeeper for data integrity and security; it handles login authentication and manages data requests from the administration page. MongoDB, a document-oriented *database*, is employed given its ability to handle the distinctive formats of data collected from TSEs and AIPSE interfaces, catering to the dynamic nature of web content and AI-generated responses. Finally, our *Administration Page* interface allows for

the real-time monitoring and analysis of collected data (see Figure 3), presenting user logs segmented by session, activity, and results, which is essential for monitoring participants in a remote observation such as this.

**Figure 2.** Online Observation Method System Architecture (created by Jong Inn Park)

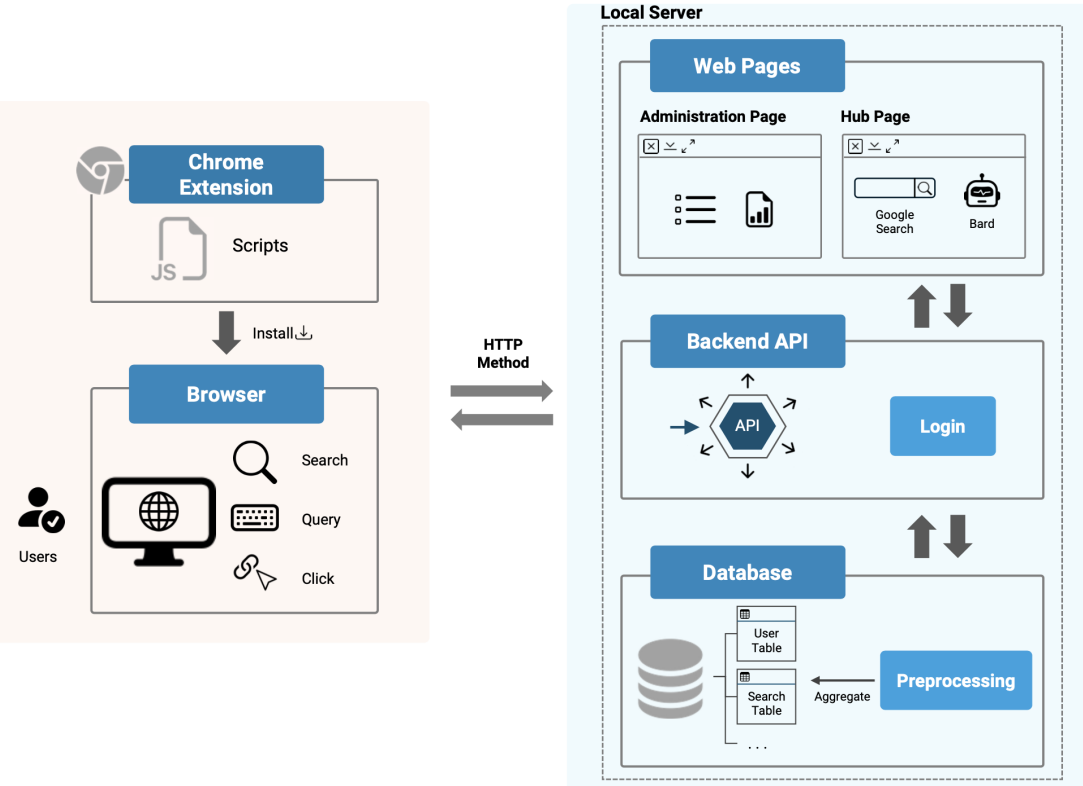
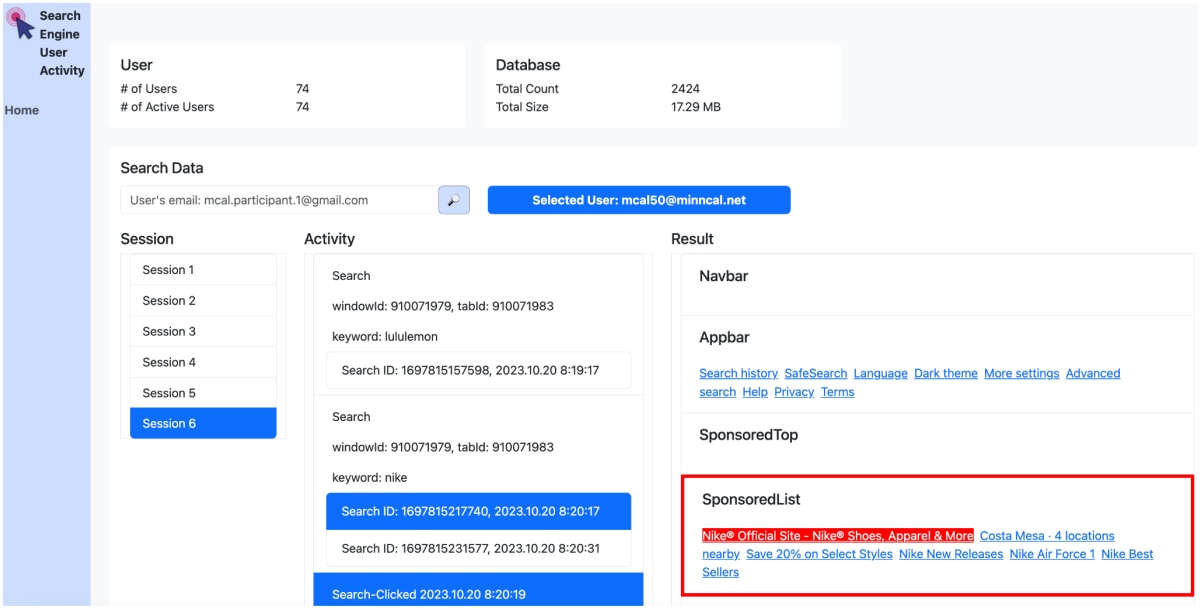


**Figure 3.** Administration Page and Example Data




### Online Search Observation Measurements

Our analysis focuses on three types of search behavior collected from our system architecture, including search engine selection, search query entered, and clicking on search result links. (1) *Search Engine Selection.* What type of search engine was used (AIPSE vs TSE) for each search episode was automatically recorded when a search was conducted. (2) *Search Query*. Participants' search queries were collected when a user successfully searched a string of words on the AIPSE or TSE platform, collecting the words used and attaching them to a unique identifier. (3) *Link-Clicking Behavior.* For each search episode, the search results – including URLs (PPC ads, organic links) and multimedia elements (knowledge graph options) for TSEs, and URLs and text responses for AIPSEs – were captured (see Figures 4 and 5). From this set of results, the system tracked which results were clicked on. This tracking includes cases in which a single search resulted in multiple options clicked on (e.g., the user clicks on a URL, presses the

back button, and subsequently clicks another URL). From this data, link-clicking behavior values were computed.

**Figure 4.** Mapping of TSE Content Options

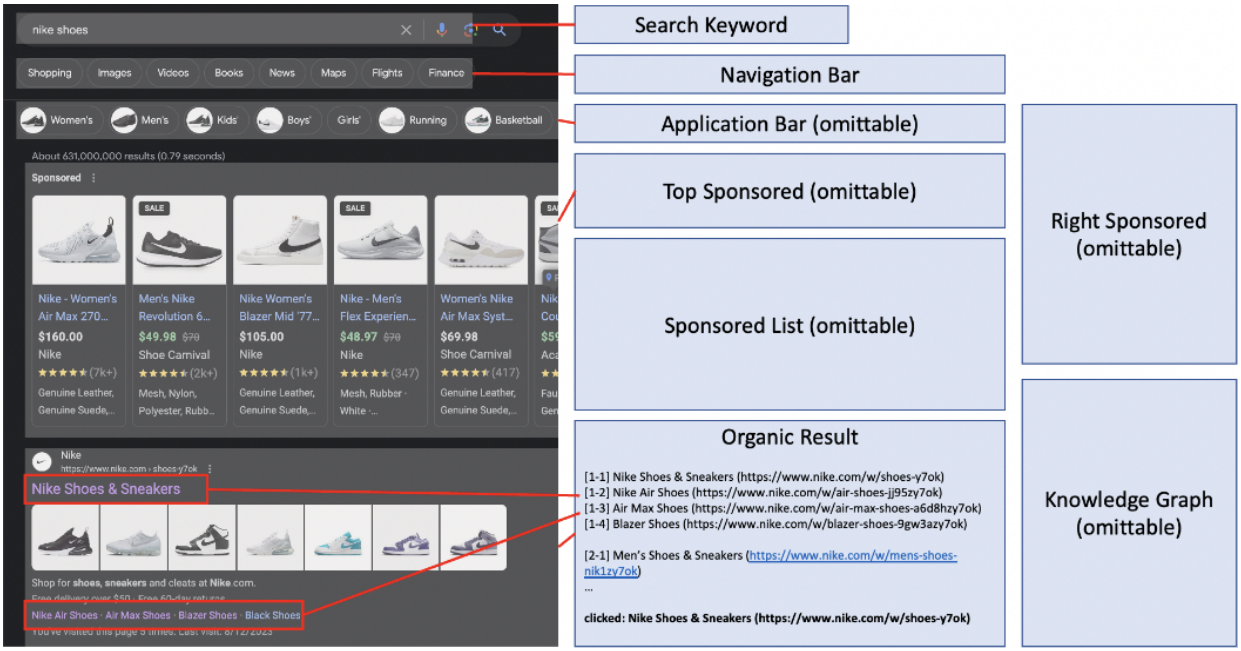
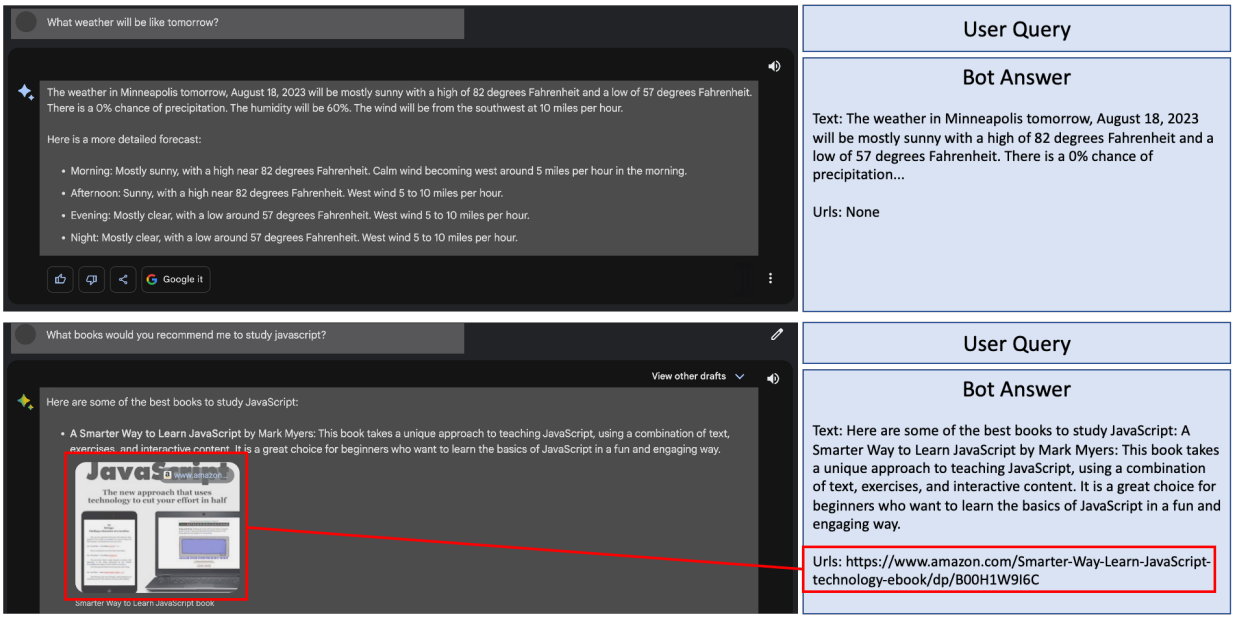



**Figure 5.** Mapping of AIPSE Content Options



Despite not being used in this study's analysis, we find it worthwhile to note that the system architecture is also able to collect temporal aspects of users' search journeys, including sessions, windows, and tabs. *Sessions.* We are also able to decipher temporal aspects of the users' search journeys by collecting timestamps for each search and dividing their searches into sessions, defined as a set of searches conducted in a period with no inactivity greater than 15 minutes (i.e., when a searcher was idle for more than 15 minutes and conducts a new search, a new session is started). *Windows and Tabs.* Finally, we were able to see how searchers divided their searches across different windows and tabs within those windows, assigning each new tab and window with a unique identifier and attaching that identifier to each search episode.

*Search Motivation.* To assess the motivation of each search episode, a computational model was developed to categorize the search queries into three categories, including (1) purchase-related motivations, (2) information-related motivations, and (3) advice-seeking motivations. Purchase-related searches are those in which products/services are explicitly mentioned in the search as directives (e.g., "IPhone 14," "Mounts for 75 in TV") or factual questions are asked about products (e.g., "Which 2024 car has the best crash test rating?" or "Where can I buy an electric bike for under $2000"). Information-related motivations are those where a consumer is attempting to gain factual information about a certain topic (except products/services) on a webpage or synopsis offered by the SE, which is similar to the way in which Broder originally conceptualized "informational" searches. Examples of information-related searches include "how long is a mile in feet?" or "when did the Revolutionary War begin?" Finally, advice-seeking motivations are ones in which consumers look to weigh options among one another (even products/services), suggest if a piece of information is correct or not,

or help in the interpreting of information – which in most cases are subjective in nature. Examples of advice-seeking searches include “How to prepare for a job interview?” or “Should I cut red meat out of my diet if my cholesterol is high?,” and “What should I consider when buying a car?” It should be noted that in all of these motivations, there is potential for both PPC and organic options to be presented on search result pages.

The computational model was developed using OpenAI’s GPT-4, which is capable of various tasks including classification problems. Typically, fine-tuning a LLM of this size is not affordable in academic labs; we instead used example data and run in-context inferences using few-shot prompting. We relied on human annotations of 200 queries to (in-context) train this model; 120 of which were generated by the research team using the definitions of the three search categories and ChatGPT Plus, and 80 of which were sourced from participants’ 623 search episodes (12.8%). Two independent undergraduate student coders annotated the search query data. Intercoder reliability (ICR) to a level of “excellent agreement beyond chance” (Cohen’s $\kappa$ = .75+; Banerjee et al., 1999, p. 6) was reached ($\kappa$ = .872) on a separate pilot data corpus of 60 searches. Once the acceptable ICR was achieved, coders annotated the 200 searches that were used to train and evaluate the model ($\kappa$ = .797). We used 15 labeled searches from the 200 student-coded searches as in-context demonstrations, with three examples for each search motivation (i.e., five cases for each search category). Performance tests were conducted on the remaining 245 labeled searches (185 + 60). The model achieved an F1-score of 86.96% and an accuracy of 87.30%. This model was used to label the remaining 543 unlabeled searches.

# CHAPTER 5: RESULTS

## Survey Sample Profile

The sample of 564 participants was balanced in terms of gender, with 50% being male (n = 282) and 47.2% being female (n = 266). The average age of respondents was 37.3 years old (SD = 12.74) ranging from 18 to 86. The respondents were predominantly White (65.4%), well-educated (51.5% with a bachelor's degree or higher), and were relatively normally distributed in terms of household income.

**Table 1.** Survey Sample Demographic Data

| Variables | Descriptive statistics |
|---|---|
| Age in years, Mean (SD) | 37.33 (12.74) |
| Gender, n (%) | |
| Male | 282 (50.0) |
| Female | 266 (47.2) |
| Non-binary | 11 (1.9) |
| Transgender | 5 (0.9) |
| Race, n (%) | |
| White | 369 (65.4) |
| Black or African | 59 (10.5) |
| Mixed race | 57 (10.1) |
| Asian | 43 (7.6) |
| Hispanic or Latino | 31 (5.5) |
| American Indian or Alaska Native | 4 (0.7) |
| Middle Eastern | 1 (0.1) |

| | |
|---|---|
| Education, n (%) | |
| Less than high school graduate | 5 (0.9) |
| High school graduate or equivalent | 77 (13.7) |
| Some college, no degree | 139 (24.6) |
| Associate's degree | 53 (9.4) |
| Bachelor's degree | 209 (37.1) |
| Master's degree | 70 (12.4) |
| Doctoral degree | 11 (2.0) |
| Household Income, n (%) | |
| Less than $14,999 | 53 (9.4) |
| $15,000 to $19,999 | 29 (5.1) |
| $20,000 to $34,999 | 75 (13.3) |
| $35,000 to $49,999 | 77 (13.7) |
| $50,000 to $74,999 | 109 (19.3) |
| $75,000 to $99,999 | 82 (14.5) |
| $100,000 to $199,999 | 111 (19.7) |
| $200,000 or more | 28 (5.0) |

**Hypotheses Testing**

To test the hypotheses (H1-H5) comparing the levels of each perception between AIPSEs and TSEs, paired t-tests were conducted using summated mean scores of each perception. Descriptive and paired t-test statistics can be found in Table 2.

For ***H1***, exploring the difference in perceived coolness between AIPSEs and TSEs, the results were in line with our hypothesis and demonstrated that AIPSEs generated significantly

higher perceived coolness (M = 5.63; SD = 1.11) than TSEs (M = 4.64; SD = 1.18) (t = 16.28; $p$ < .001). For ***H2,*** we hypothesized that perceived social presence would be higher for AIPSEs than TSEs, which was supported by the evidence. Specifically, AIPSEs garnered significantly higher perceived social presence (M = 4.76; SD = 1.33) than TSEs (M = 3.25, SD = 1.49) (t = 20.73; $p$ < .001). The findings from ***H3,*** testing the difference in perceived responsiveness between AIPSEs and TSEs, were also in line with our predictions, with results showing that AIPSEs garnered significantly higher perceived responsiveness (M = 5.37; SD = 1.06) than TSEs (M = 4.91; SD = 1.2) (t = 7.31; $p$ < .001).

In ***H4***, we hypothesized that TSEs would be perceived as higher in variety compared to AIPSEs, which was confirmed. TSEs received a mean score of 5.90 (SD = 0.89) for perceived variety, while AIPSEs received a mean score of 4.93 (SD = 1.22), and the difference was statistically significant (t = -16.9; $p$ < .001). Finally, testing ***H5,*** the difference in perceived ease of use between AIPSEs and TSEs was contrary to our hypothesis. The result showed that TSEs generated higher perceived ease of use (M = 5.94; SD = .98) than AIPSEs (M = 5.10; SD = 1.22) (t = -14.09; $p$ < .001). In sum, all hypotheses proposed were supported by the t-test results, except for ***H5***.

**Table 2.** Paired T-test Results (H1-H5)

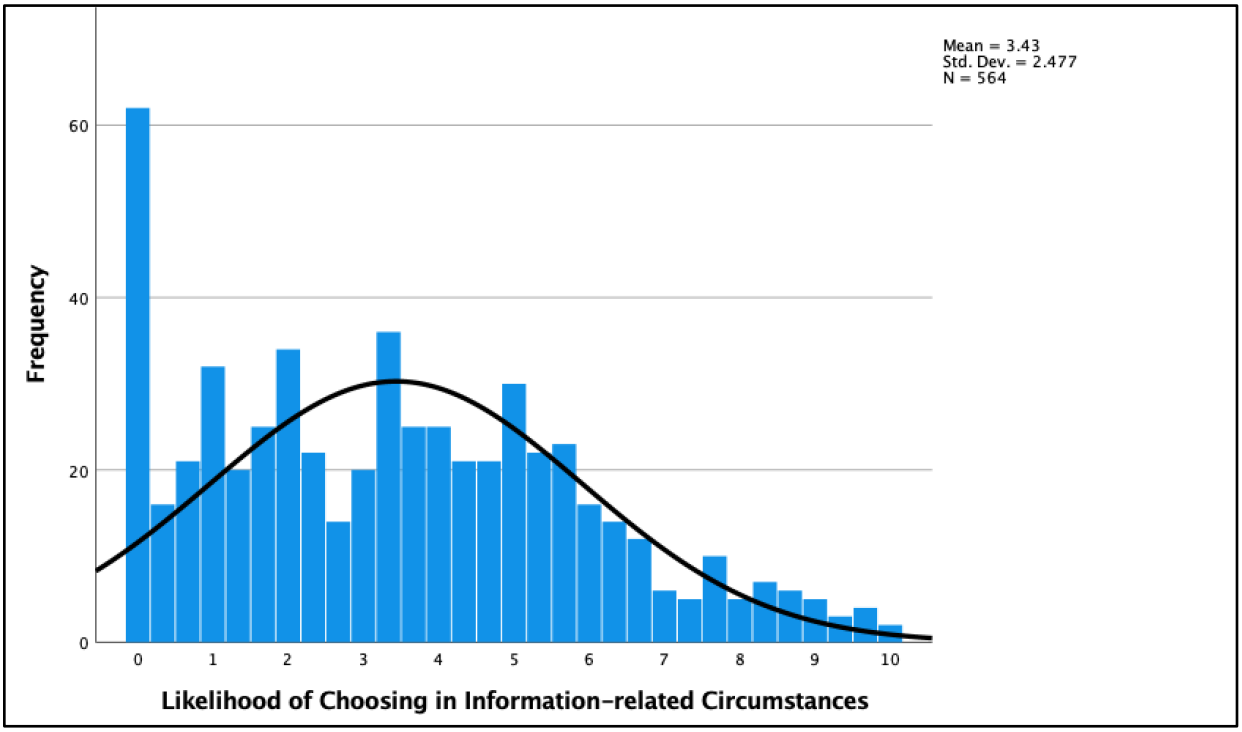
| Perception variables | AIPSE mean | TSE mean | T-value |
|---|---|---|---|
| Perceived coolness | 5.63 | 4.64 | 16.28*** |
| Perceived social presence | 4.76 | 3.25 | 20.73*** |
| Perceived responsiveness | 5.37 | 4.91 | 7.31*** |
| Perceived variety | 4.93 | 5.90 | -16.9*** |
| Perceived ease of use | 5.10 | 5.94 | -14.09*** |

***$p$ <.001

### *RQ1: Relationship between Perceptions and Likelihood of Choosing AIPSE over TSE*

Examining connections between the affordance perceptions and the likelihood of choosing an AIPSE over a TSE, we conducted separate hierarchical regression on the dependent variable in three search motivation situations, because the likelihood of choosing AIPSEs over TSEs was measured for three types of search motivations. Before running the regression, first, paired t-tests were conducted to compare the likelihood of choosing an AIPSE over a TSE across the three search motivation categories. Results revealed significant differences in the likelihood of choosing AIPSEs depending on search motivations. Individuals' likelihood of choosing an AIPSE over a TSE was highest for advice-seeking motivation ($M = 4.9$; $SD = 2.73$), which was significantly higher than the likelihood of choosing an AIPSE in the information-seeking search situation ($M = 3.43$; $SD = 2.48$; $t = 16.05$; $p < .001$) and purchase-related search ($M = 1.86$; $SD = 1.75$; $t = 26.35$; $p < .001$). The likelihood of choosing an AIPSE in the information-seeking search situation was significantly higher than for purchase-related searches ($t = 15.93$; $p < .001$) (see Figures 6, 7, and 8).

**Figure 6.** Distribution of Likelihood of Choosing an AIPSE vs TSE in Information-related Searches




Note for Figures 6, 7 and 8: 0 indicates preference for TSE over AIPSE, whereas 10 indicates preference for AIPSE over TSE (5 indicates equal preference)

**Figure 7.** Distribution of Likelihood of Choosing an AIPSE vs TSE in Advice-seeking Searches

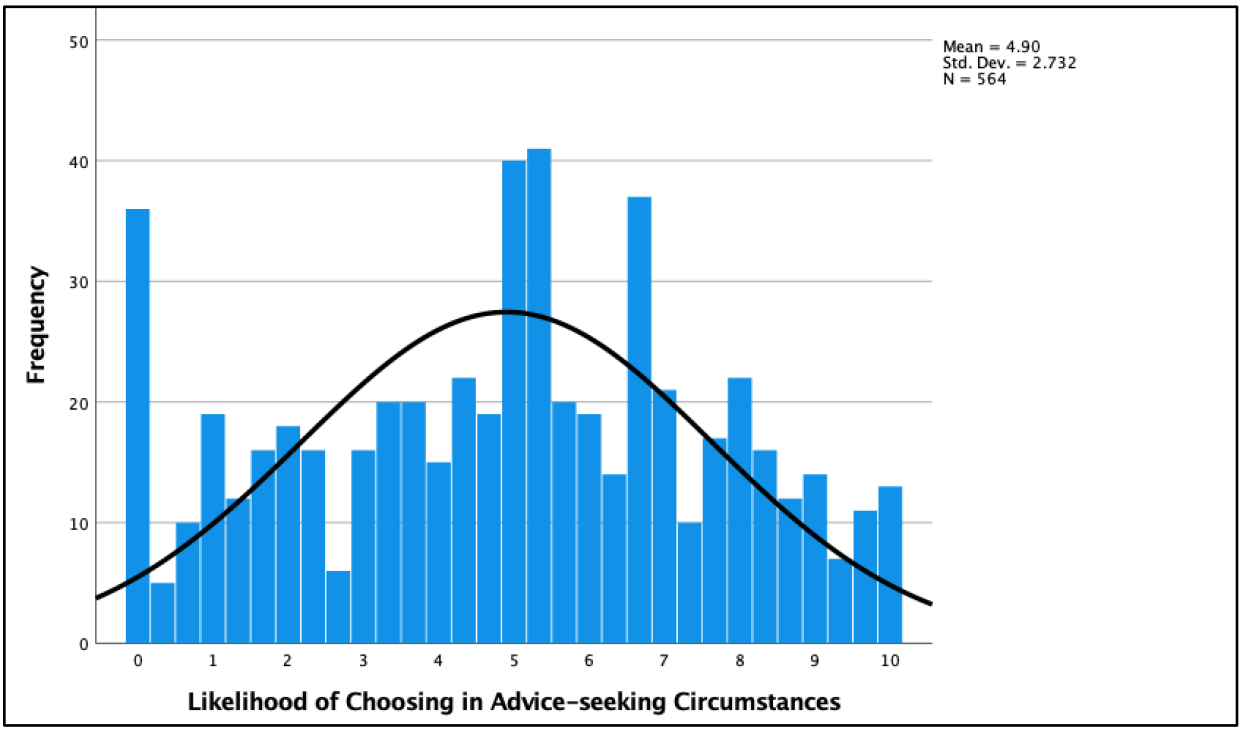
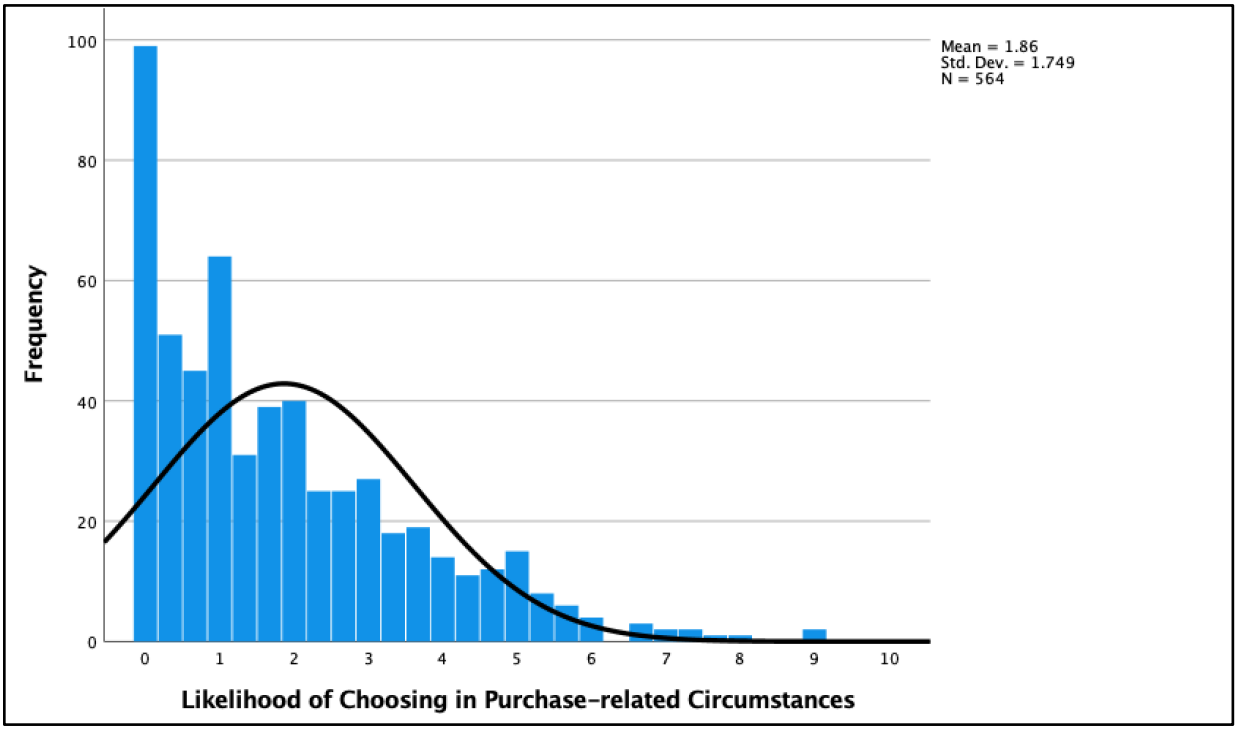



**Figure 8.** Distribution of Likelihood of Choosing an AIPSE vs TSE in Purchase-related Searches



The separate regression analyses revealed interestingly different patterns across the three search motivation categories in the relationship between search engine perceptions and the likelihood of choosing AIPSEs over TSEs. In each of the three models, predictors were entered into two separate blocks using the stepwise method, with the first block being composed of demographic variables (age, gender, race, education, and income) to control for, and the second containing the affordance perception variables (perceived coolness, social presence, responsiveness, variety, and ease of use) for each SE. First, in the purchase-related search situations – which showed the lowest level of choosing an AIPSE over a TSE – age appeared significantly related to the dependent variable in the initial model considering the demographic variables (**β** = .098); however, it became non-significant when the perception variables were entered. In the final model, perceived responsiveness of TSEs (**β** = -.307) was negatively related to the dependent variable, whereas perceived social presence of TSEs (**β** = .363) and perceived variety of AIPSEs (**β** = .208) were positively related. The regression model explained about 15% of the variance in the dependent variable (see Table 3).

**Table 3.** Hierarchical Regression for Predicting Likelihood of Choosing an AIPSE over a TSE for Purchase-related Search (RQ1)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | Age | .098* |
| | Adjusted R square | .008 |
| | df = 1; MS = 16.7; F = 5.5; p = .019 | |
| Model 2 | Age | .055 |
| | Perceived social presence of TSEs | .363*** |
| | Perceived responsiveness of TSEs | -.307*** |
| | Perceived variety on AIPSEs | .208*** |
| | Adjusted R square | .147*** |
| | df = 4; MS = 65.89; F = 25.24; $p < .001$ | |

*$p$ < .05, **$p$ < .01, ***$p$ <.001
*, **, *** for Adjusted R Square indicates significance of R-squared increments
Note: Only significant variables shown, others omitted

The regression model for the information-seeking situation explained over 18% of the variance in the dependent variable and included three significant predictors (see Table 4). Perceived social presence of AIPSEs (**β** = .265) and perceived ease of use of AIPSEs (**β** = .229) were positively related to choosing an AIPSE over a TSE, while perceived responsiveness of TSEs (**β** = -.184) was negatively related. Lastly, the regression model predicting the likelihood of choosing an AIPSE in the advice-seeking situation, which showed the highest level of AIPSE selection, included five significant predictors. Perceived social presence of AIPSEs (**β** = .220), perceived coolness of AIPSEs (**β** = .200), and perceived responsiveness of AIPSEs (**β** = .155) were positively related to the dependent variable. In contrast, perceived social presence of TSEs (**β** = -.178) and perceived variety on TSEs (**β** = -.106) negatively predicted the dependent variable (see Table 5). This model explained 28% of the variance in the dependent variable.

**Table 4.** Hierarchical Regression for Predicting Likelihood of Choosing an AIPSE over a TSE for Information-related Search (RQ1)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | No significant predictor among demographics | |
| Model 2 | Perceived social presence of AIPSEs | .265*** |
| | Perceived ease of use of AIPSEs | .229*** |
| | Perceived responsiveness of TSEs | -.184*** |
| | Adjusted R square | .184*** |
| | df = 3; MS = 216.41; F = 43.21; $p$ < .001 | |

*$p$ < .05, **$p$ < .01, ***$p$ <.001
*, **, *** for Adjusted R Square indicates significance of R-squared increments

**Table 5.** Hierarchical Regression for Predicting Likelihood of Choosing an AIPSE over a TSE for Advice-seeking Search (RQ1)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | No significant predictor among demographics | |
| Model 2 | Perceived social presence of AIPSEs | .220*** |
| | Perceived coolness of AIPSEs | .200** |
| | Perceived social presence of TSEs | -.178*** |
| | Perceived responsiveness of AIPSEs | .155* |
| | Perceived variety on TSEs | -.106* |
| | Perceived coolness of TSEs | -.097 |
| | Adjusted R square | .276* |
| | df = 6; MS = 198.46; F = 36.72; $p < .001$ | |

*$p < .05$, **$p < .01$, ***$p < .001$
*, **, *** for Adjusted R Square indicates significance of R-squared increments

***RQ2: Relationship between Awareness of Hallucination and (2.1) AIPSE Perceptions and (2.2) Likelihood of Choosing AIPSE over TSE***

To examine the relationship between hallucination awareness and AIPSE perceptions, a series of hierarchical regression analyses were conducted with demographic variables entered into the first block and awareness of hallucination entered into the second block, for each of the five AIPSE affordance perceptions as the dependent variable. Only two of the five models contained any significant predictors, with one significant demographic predictor in each. For the model predicting perceptions of AIPSE perceived ease of use (**β** = .092; p = .028) and the model for predicting perceptions of AIPSE variety (**β** = .170; p < .001), age was the only predictor shown to be significant in each of the models. Similarly, for the relationship between hallucination awareness and likelihood of choosing an AIPSE over a TSE in each of the three motivational states, only the purchase-related motivation model had significant results, with age being the only significant predictor in the model (**β** = .098; p = .019). The results suggest that

individuals' awareness of hallucination is not related to their affordance perceptions of AIPSEs or their choice between AIPSEs and TSEs. (see Tables 6, 7, and 8).

**Table 6.** Hierarchical Regression for Predicting Perceived Ease of Use of AIPSEs with Awareness of Hallucination (RQ2.1)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | Age | .092* |
| | Adjusted R square | .007 |
| | df = 1; MS = 7.11; F = 4.84; p = .028 | |
| Model 2 | Awareness of Hallucination was non-significant | |

*$p < .05$, ** $p < .01$, ***$p < .001$

**Table 7.** Hierarchical Regression for Predicting Perceived Variety on AIPSEs with Awareness of Hallucination (RQ2.1)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | Age | .17*** |
| | Adjusted R square | .027 |
| | df = 1; MS = 24.06; F = 16.71; p < .001 | |
| Model 2 | Awareness of Hallucination was non-significant | |

*$p < .05$, **$p < .01$, ***$p < .001$

**Table 8.** Hierarchical Regression for Predicting Likelihood of Choosing an AIPSE over a TSE in Purchase-related Searches with Awareness of Hallucination (RQ2.2)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | Age | .098* |
| | Adjusted R square | .008 |
| | df = 1; MS = 16.7; F = 5.5; p = .019 | |
| Model 2 | Awareness of Hallucination was non-significant | |

*$p < .05$, **$p < .01$, ***$p < .001$

**Web Data Sample Profile**

The following three research questions (RQ3, RQ4, and RQ5) focus on individual-level data from the 39 participants who provided us with usable web data, analyzing relationships between their survey responses and their aggregate web behavior (i.e., total clicks, average

keyword length, search engine selection, etc.). The sample of 39 participants was balanced in terms of gender, with 46.1% being male (n = 18) and 43.6% being female (n = 17). The average age of respondents was 36.1 years old (SD = 12.37) ranging from 20 to 68. The respondents were predominantly White (71.8%) and well-educated (43.7% with a bachelor's degree or higher) (see Table 9). The next set of three research questions (RQ6, RQ7, and RQ8) use the individual search episodes produced by these 39 participants as the unit of analysis. The 39 respondents produced 623 unique search episodes, 465 of which were conducted on a TSE (74.5%). Dividing these searches by underlying motivation, 329 were information-related, 137 were advice-seeking, and 157 were purchase-related. Parsing these categories further, 257 of the information-related searches (78.1%), 65 of the advice-seeking searches (47.4%), and 143 of the purchase-related searches (91.1%) were conducted on a TSE.

**Table 9.** Survey Sample Demographic Data

| Variables | Descriptive statistics |
|---|---|
| Age in years, Mean (SD) | 36.08 (12.37) |
| Gender, n (%) | |
| Male | 18 (46.1) |
| Female | 17 (43.6) |
| Non-binary | 3 (7.7) |
| Transgender | 1 (2.6) |
| Race, n (%) | |
| White | 28 (71.8) |
| Asian | 5 (12.8) |
| Mixed race | 3 (7.7) |

| | |
|---|---|
| Hispanic or Latino | 2 (5.1) |
| Black or African | 1 (2.6) |
| Education, n (%) | |
| High school graduate or equivalent | 4 (10.3) |
| Some college, no degree | 12 (30.8) |
| Associate's degree | 6 (15.4) |
| Bachelor's degree | 12 (30.8) |
| Master's degree | 4 (10.4) |
| Doctoral degree | 1 (2.6) |
| Household Income, n (%) | |
| Less than $14,999 | 2 (5.1) |
| $15,000 to $19,999 | 2 (5.1) |
| $20,000 to $34,999 | 6 (15.4) |
| $35,000 to $49,999 | 9 (23.1) |
| $50,000 to $74,999 | 10 (25.6) |
| $75,000 to $99,999 | 2 (5.1) |
| $100,000 to $199,999 | 7 (17.9) |
| $200,000 or more | 1 (2.6) |

***RQ3 – RQ5: Relationship between AIPSE / TSE perceptions and (RQ3) search engine selection, (RQ4) average keyword length, and (RQ5) link-clicking behavior***

To investigate how the perceptions about AIPSEs and TSEs may affect the proportion with which SEs are selected (RQ3), a proportion variable was constructed by dividing the total number of searches using AIPSEs by the total number of searches a user conducted (i.e., if a user

searched 16 total times, 10 of which were on an AIPSE, their proportion would be .625). The mean proportion of AIPSE selection over the 39 users was .22 (SD = .297). To test this relationship, a hierarchical regression model was constructed using the stepwise method, first entering demographic variables and then entering the five perception variables for both AIPSEs and TSEs. No demographic or perception variables were significant in the model.

Moving to the model investigating the relationship between perceptions of responsiveness on AIPSEs / TSEs and average keywords used (RQ4), another hierarchical regression model was used, first entering demographic variables and then entering AIPSE and TSE responsiveness perception values. This model explained only 7.7% of the variance in the dependent variable, with a single demographic variable, gender, being negatively associated with keyword length (**β** = -.318) (see Table 10).

**Table 10.** Hierarchical Regression for Predicting Keyword Length with Perceptions of Responsiveness on AIPSEs and TSEs (RQ4)

| Model | Predictors | Std. Beta |
|---|---|---|
| Model 1 | Gender (male) | -.318* |
| | Adjusted R square | .077 |
| | df = 1; MS = 33.33; F = 4.16; p = .049 | |
| Model 2 | No significant predictor among perceptions | |

*$p < .05$, **$p < .01$, ***$p < .001$

Finally, a hierarchical regression analysis investigating the relationship between perceptions of variety and responsiveness on AIPSEs / TSEs and link-clicking behavior (RQ5) was conducted in the same manner as the previous two. Given that we are using aggregate user data (i.e., behavior from a user over their total 24-hour search period), the dependent variable was computed by summing the total number of clicks a user executed throughout all searches in the 24-hour period. No demographic or perception variables were significant in the model.

***RQ6: Relationship between search motivation and selection of TSEs vs AIPSEs***

Turning our attention to the analysis of the 623 search episodes, and specifically the differences in the number of times each SE type was selected across search motivation, a chi-square test was conducted. Results show that TSEs were used more frequently than AIPSEs in both information-related and purchase-related searches (78.1% and 91.1% of the time respectively); yet, AIPSEs were more frequently relied on in advice-seeking circumstances (52.6% of the time). These differences in selection between the groups were statistically significant ($\chi^2$ = 78.05; Cramer's V = .354) (see Table 11).

**Table 11.** Chi-square Results for SE Selection Across Search Motivations (RQ6)

| Motivation | TSE Selection | AIPSE Selection | $\chi^2$ | Cramer's V |
|---|---|---|---|---|
| Information-related | 257 | 72 | | |
| Advice-seeking | 65 | 72 | 78.05*** | .354*** |
| Purchase-related | 143 | 14 | | |

*$p$ <.05, **$p$ <.01, ***$p$ <.001

***RQ7: Relationship between search motivation and keyword length on AIPSEs vs. TSEs***

Next, examining keyword length differences between AIPSEs and TSEs across the three types of search motivation, four sets of independent samples t-tests were conducted, examining: (RQ7.1) differences in keyword length by SE type; (RQ7.2) differences in keyword length by search motivation; (RQ7.3) differences in keyword length between motivations controlling for SE type (i.e., keyword length differences between information and purchase-related searches on TSEs); and (RQ7.4) keyword length differences between SE types controlling for search motivation (i.e., keyword length differences on AIPSEs and TSEs in purchase-related searches). Given the difference in sample size between these two groups, and the violation of Levene's test

for equality of variances across all four t-tests, Welch's t-test values were used for all subsequent analyses to assess group differences unless specified otherwise.

The first t-test examined differences in keyword length (i.e., # of words in each search query) by SE type alone. Within the sample, AIPSEs had a much higher average keyword length (M = 11.35; SD = 9.8) compared to TSE keyword length (M = 4.11; SD = 3.45), which was a statistically significant difference (t = 9.11; p < .001) (see Table 12) (see Figures 9 and 10).

**Table 12.** Independent Samples Welch's T-test Results (RQ7.1)

| SE Type | n | # of words (mean) | T-value |
|---|---|---|---|
| AIPSE | 158 | 11.35 | 9.11*** |
| TSE | 465 | 4.11 | |

****p* <.001

**Figure 9.** TSE Keyword Length Distribution

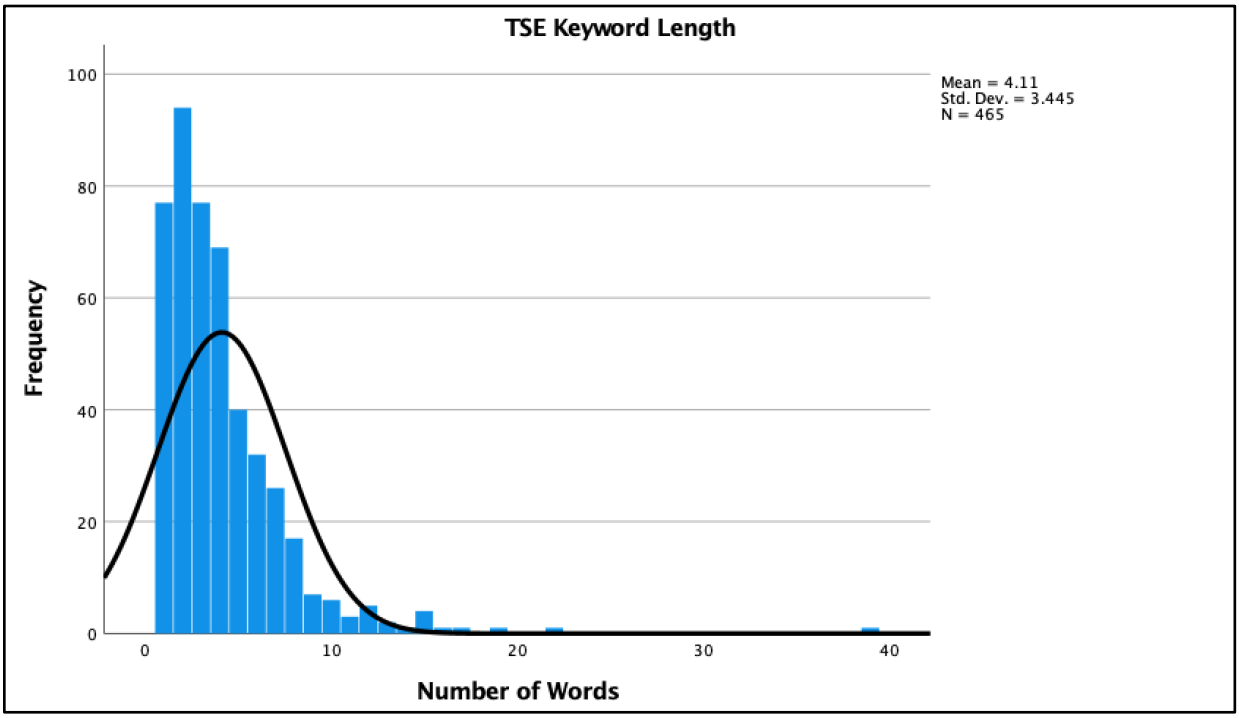
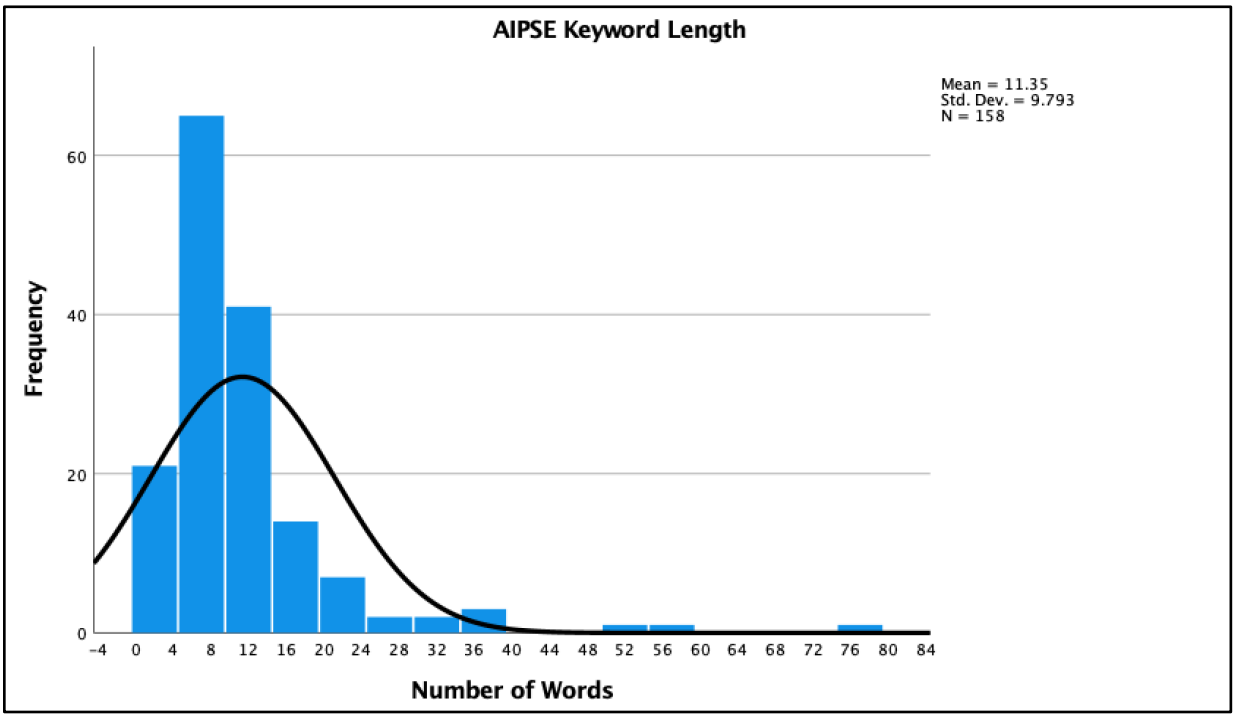


**Figure 10.** AIPSE Keyword Length Distribution




The second set compares differences in keyword length by search motivation only. Comparing information-related search keyword lengths (M = 4.66; SD = 4.64) to advice-seeking (M = 11.8; SD = 9.66; t = -8.26; p < .001) and purchase-related (M = 3.54; SD = 2.36; t = 3.52; p < .001) keyword lengths, differences were significant in each of these pairwise comparisons. Comparing advice-seeking searches to purchase-related searches, differences in keyword lengths were also significant (t = 9.75; p < .001) (see Table 13).

**Table 13.** T-test Results for Differences in Keyword Length Between Motivations (RQ7.2)

| Search Motivation | n | # of words (mean) | T-value |
|---|---|---|---|
| Information-related | 329 | 4.66 | -8.26*** |
| Advice-seeking | 137 | 11.8 | |
| Information-related | 329 | 4.66 | 3.52*** |
| Purchase-related | 157 | 3.54 | |
| Advice-seeking | 137 | 11.8 | 9.75*** |

| | | |
|---|---|---|
| Purchase-related | 157 | 3.54 |

*$p < .05$, **$p < .01$, ***$p < .001$

Investigating differences in keyword length between different motivations while controlling for SE type, independent samples t-tests were conducted within each SE type. Findings reveal that advice-seeking searches on TSEs (M = 8.55; SD = 3.72) were significantly longer than both information-related searches (M = 3.49; SD = 3.28; t = -10.02; p < .001) and purchase-related searches (M = 3.2; SD = 1.6; t = 11.15; p < .001) on TSEs. The keyword length difference between information- and purchase-related searches on TSEs, however, was not significantly different. This same pattern emerged between search motivations on AIPSEs, where advice-seeking searches (M = 14.72; SD = 12.16) were significantly longer than both information-related searches (M = 8.82; SD = 6.18; t = -3.67; p < .001) and purchase-related searches (M = 7.07; SD = 4.92; t = 2.31; p = .023); yet, the keyword length difference between information- and purchase-related searches was not significantly different (see Table 14).

**Table 14.** T-test Results for Differences in Keyword Length Between Motivations Controlling for SE Type (RQ7.3)

| Motivation within SE Type | n | # of words (mean) | T-value |
|---|---|---|---|
| Information-related TSE | 257 | 3.49 | -10.02*** |
| Advice-seeking TSE | 65 | 8.55 | |
| Information-related TSE | 257 | 3.49 | 1.22 |
| Purchase-related TSE | 143 | 3.2 | |
| Advice-seeking TSE | 65 | 8.55 | 11.15*** |
| Purchase-related TSE | 143 | 3.2 | |
| Information-related AIPSE | 72 | 8.82 | -3.67*** |
| Advice-seeking AIPSE | 72 | 14.72 | |
| Information-related AIPSE | 72 | 8.82 | 1.16‡ |
| Purchase-related AIPSE | 14 | 7.07 | |
| Advice-seeking AIPSE | 72 | 14.72 | 2.31*‡ |
| Purchase-related AIPSE | 14 | 7.07 | |

*p <.05, **p <.01, ***p <.001
‡ denotes no violation of Levene's test for Equality of Variances, Welch's values not used

Finally, differences in keyword length were compared between SEs while controlling for search motivation by t-tests. The first analysis tested differences in keyword length on AIPSEs (M = 8.82; SD = 6.18) and on TSEs (M = 3.49; SD = 3.28) in information-related search circumstances, which was statistically significant (t = 7.04; p < .001). Next, the difference in keyword length between the two types of SEs within the advice-seeking search situations was statistically significant: AIPSEs (M = 14.74; SD = 12.16) and TSEs (M = 8.55; SD = 3.72) (t = 4.1; p < .001). Finally, keyword length difference in the purchase-related search situations were examined, with results showing that the average keyword length on AIPSEs (M = 7.07; SD = 4.92) was significantly greater than that on TSEs (M = 3.2; SD = 1.6) (t = 2.93; p = .011) (see Table 15).

**Table 15.** T-test Results for Differences in Keyword Length Between AIPSE and TSE Controlling for Search Motivation (RQ7.4)

| SE Type within Search Motivation | n | # of words (mean) | T-value |
|---|---|---|---|
| Information-related AIPSE | 72 | 8.82 | 7.04*** |
| Information-related TSE | 257 | 3.49 | |
| Advice-seeking AIPSE | 72 | 14.72 | 4.1*** |
| Advice-seeking TSE | 65 | 8.55 | |
| Purchase-related AIPSE | 14 | 7.07 | 2.93* |
| Purchase-related TSE | 143 | 3.2 | |

*p <.05, **p <.01, ***p <.001

***RQ8: Relationship between search motivation and link-clicking behavior***

For addressing RQ8, link-clicking behavior was computed as a dichotomous variable with the values indicating whether any link-clicking occurred in each search episode. Following

the analysis approach used above, we conducted four chi-square tests for differences in link-clicking behavior, investigating; (RQ8.1) differences in link-clicking behavior between SE type; (RQ8.2) differences in link-clicking behavior between motivations; (RQ8.3) differences in link-clicking behavior between motivations while controlling for SE type; and (RQ8.4) differences in link-clicking behavior between SE types controlling for search motivation. Due to unforeseen changes to the backend of Google Bard in the middle of one wave of our web observation data collection, we experienced minor data loss in terms of tracking the number of links that were presented to users after an AIPSE search. This loss in tracking affects our ability to compute the ratio of the number of linked options clicked to the total number of linked options presented, forcing us to use the number of link-clicks rather than the ratio data.

We begin by analyzing clicking behavior by SE type, finding that differences in clicking on links were significantly different between AIPSEs and TSEs ($\chi^2 = 105.04$; $p < .001$; Cramer's V = .411), with TSEs commanding a far larger portion of clicks (see Table 16), which is not surprising given that there are many more link options in TSE results than in AIPSE results.

**Table 16.** Chi-square Results for Link-Clicking Behavior Between SE type (RQ8.1)

| SE Type | No click | Click | $\chi^2$ | Cramer's V |
|---|---|---|---|---|
| AIPSE | 139 | 19 | 105.04*** | .411*** |
| TSE | 190 | 275 | | |

*$p < .05$, **$p < .01$, ***$p < .001$

Next, to analyze the presence or absence of clicks across the three different search motivations, three chi-square tests were conducted. The first analyzed the difference in presence/absence of clicks in information-related and advice-seeking searches, finding that there was no statistically significant difference in link-clicking behavior between these groups. In

contrast, when investigating the difference in link-clicking behavior between information-related and purchase-related searches, the difference was significant ($\chi^2 = 18.51$; $p < .001$; Cramer's V = .195). Finally, with respect to the presence and absence of clicks in advice-seeking and purchase-related searches, the difference was significant as well ($\chi^2 = 22.69$; $p < .001$; Cramer's V = .278) (see Table 17).

**Table 17.** Chi-square Results for Link-Clicking Behavior Between Motivations (RQ8.2)

| Search Motivation | No click | Click | $\chi^2$ | Cramer's V |
|---|---|---|---|---|
| Information-related | 186 | 143 | 1.94 | -.064 |
| Advice-seeking | 87 | 50 | | |
| Information-related | 186 | 143 | 18.51*** | .195*** |
| Purchase-related | 56 | 101 | | |
| Advice-seeking | 87 | 50 | 22.69*** | .278*** |
| Purchase-related | 56 | 101 | | |

*$p < .05$, **$p < .01$, ***$p < .001$

Examining differences in link-clicking behavior between motivations while controlling for SE type, six chi-square tests were conducted. Within TSE searches, significant differences were found between (1) information-related and advice-seeking searches ($\chi^2 = 4.34$; $p = .037$; Cramer's V = .116); and (2) information- and purchase-related searches ($\chi^2 = 11.52$; $p < .001$; Cramer's V = .170). The difference in link-clicking behavior between advice-seeking and purchase-related searches on TSEs was not significant (see Table 18). Conversely, looking at AIPSE link-clicking behavior between motivations, no significant differences were observed between motivation group comparisons.

**Table 18.** Chi-square Results for Link-Clicking Behavior Between Search Motivations Controlling SE Type (RQ8.3)

| Motivation within SE Type | No click | Click | $\chi^2$ | Cramer's V |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Information-related TSE | 124 | 133 | 4.34* | .166* |
| Advice-seeking TSE | 22 | 43 | | |
| Information-related TSE | 124 | 133 | 11.52*** | .170*** |
| Purchase-related TSE | 44 | 99 | | |
| Advice-seeking TSE | 22 | 43 | .195 | .031 |
| Purchase-related TSE | 44 | 99 | | |
| Information-related AIPSE | 62 | 10 | .600 | -.065 |
| Advice-seeking AIPSE | 65 | 7 | | |
| Information-related AIPSE | 62 | 10 | .002 | .004 |
| Purchase-related AIPSE | 12 | 2 | | |
| Advice-seeking AIPSE | 65 | 7 | .261 | .055 |
| Purchase-related AIPSE | 12 | 2 | | |

*$p < .05$, **$p < .01$, ***$p < .001$

Finally, three chi-square tests were conducted to examine link-clicking behavior differences between SE types while controlling for search motivation. The first analyzed the difference between information-related searches on TSEs and information-related searches on AIPSEs, which was found to be significant ($\chi^2 = 32.81$; Cramer's V = -.316). Next, a significant difference in link-click behavior was found between advice-seeking searches on TSEs and advice-seeking searches on AIPSEs ($\chi^2 = 46.94$; Cramer's V = -.585). Finally, with respect to purchase-related searches on TSEs and purchase-related searches on AIPSEs, the difference was also significant ($\chi^2 = 16.78$; Cramer's V = -.327) (see Table 19); however, this final set of results should be taken with caution given the cell count for link-click behavior in purchase-related AIPSE searches was below 5.

**Table 19.** Chi-square Results for Link-Clicking Behavior Between SE Type Controlling for Search Motivation (RQ8.4)

| Motivation * SE Type | No click | Click | $\chi^2$ | Cramer's V |
|---|---|---|---|---|
| Information-related TSE | 124 | 133 | 32.81*** | -.316*** |
| Information-related AIPSE | 62 | 10 | | |

| | | | | |
|---|---|---|---|---|
| Advice-seeking TSE | 22 | 43 | 46.94*** | -.585*** |
| Advice-seeking AIPSE | 65 | 7 | | |
| Purchase-related TSE | 44 | 99 | 16.78*** | -.327*** |
| Purchase-related AIPSE | 12 | 2 | | |

*$p < .05$, **$p < .01$, ***$p < .001$

# CHAPTER 6: DISCUSSION

## *Summary of Findings*

The rapid emergence and adoption of AIPSEs and other generative AI tools by both those in industry and individuals present enormous opportunities and challenges for the future of research on SE use behavior and advertising alike. To address the opportunities and challenges, this exploratory study examined several relationships centering around perceptions of different technological affordances offered by AIPSEs and TSEs, motivations for using each type of SE, behavioral intentions to use each in the future, and actual use behavior. The study results provide several notable findings that expand upon the prior research employing TIME, MAIN, and uses and gratifications, along with those that offer practical implications for future research investigating behavior on AIPSEs and what place paid advertising may have on these platforms.

**Table 20.** Summary of Findings

| Hypotheses and Research Questions | Finding | Implications |
|---|---|---|
| H1: AIPSEs will likely generate higher perceived coolness compared to TSEs | Supported | Given findings from prior TIME research, these perceptions may be linked to positive reactions and engagement with AIPSEs, more trust in and/or loyalty toward them, and increased expectations for these platforms |
| H2: AIPSEs will likely generate higher perceived social presence compared to TSEs | Supported | |
| H3: AIPSEs will likely generate higher perceived responsiveness compared to TSEs | Supported | |

| | | |
|---|---|---|
| H4: TSEs will likely generate higher perceived variety compared to AIPSEs | Supported | Variety in certain circumstances may be linked to higher likelihood of clicking on hyperlinked options – this could be a reason to increase variety on AIPSEs |
| H5: AIPSEs will likely generate higher perceived ease of use compared to TSEs | Not supported | Not unexpected given consumers have more experience with TSEs, which may make them feel more at ease when navigating |
| RQ1: How are the perceptions about AIPSEs and TSEs related to the likelihood of choosing AIPSEs over TSEs? | Perceived social presence emerged as the most consistent predictor of the likelihood of choosing AIPSEs over TSEs across all three search motivation categories | Social presence is not necessarily tied to one affordance alone, but rather a conglomerate (i.e., presentation of information, the quickness of the system, and tone – may be a good indicator of how a collection of features can influence the affordance perceptions |
| RQ2: How is one's awareness of hallucination on AIPSEs related to (2.1) the perceptions about AIPSE affordances; and (2.2) their likelihood of choosing AIPSEs over TSEs? | We were unable to find any significant relationship between any of the AIPSE perceptions or likelihood of choosing an AIPSE and awareness of hallucination | Surprising given the implications of hallucination on the results one obtains from an AIPSE, yet positive in terms of potential future adoption rates among individuals who are aware of its shortcomings |
| RQ3: How are the different perceptions about AIPSEs and TSEs related to search engine selection, and which perceptions are most strongly related? | These relationships were again non-significant, albeit gender being a negative significant predictor of keyword length | A potential explanation for the lack of significant relationships between AIPSE / TSE perceptions and the dependent variables in these models stems from the small |

| | | |
|---|---|---|
| RQ4: How are the responsiveness perceptions about AIPSEs and TSEs related to the length of one's queries on TSEs vs AIPSEs? | | sample size of 39 participants from which we were able to connect survey responses to the online search observation data |
| RQ5: How are the responsiveness and variety perceptions about AIPSEs and TSEs related to link-clicking behavior on TSEs vs AIPSEs? | | |
| RQ6: How is the selection of TSEs vs AIPSEs affected by search motivation? | TSEs were used more frequently than AIPSEs in our results, yet AIPSE searches did make up over a quarter of the total searches conducted | Increased reliance on AIPSEs could significantly impact the number of searches conducted on Google (or other TSEs), which could then influence the effectiveness of certain sponsored campaigns as a product of less search volume |
| RQ7: How is keyword length on TSEs vs AIPSEs affected by search motivation? | There is little overlap in the way users form their queries on AIPSEs vs TSEs, with AIPSEs using 7 more keywords per search on average compared to TSEs. Additionally, advice-seeking searches resulted in much more elaborative keyword use than purchase- or information-related searches | If advertisers aim to connect with consumers on AIPSEs – which is likely given its quick adoption and potential to disrupt TSE use – it is likely that new tactics will need to be devised to disseminate sponsored content |

| | | |
|---|---|---|
| RQ8: How is link-clicking behavior on TSEs vs AIPSEs affected by search motivation? | Purchase-related searches are the ones that consumers will be most likely to click on, but advice-seeking searches may also provide traffic to websites alongside purchase-related searches | Given that AIPSEs do not offer as many links as TSEs, if AIPSEs increase their link content they may be able to generate enough traffic to purchase-related websites to justify the implementation of an advertising model on AIPSEs |

First, findings indicate significant differences in the five perception heuristics between AIPSEs and TSEs. Specifically, support was found for the hypotheses that the unique technological affordances of AIPSEs would generate higher perceived coolness (H1), social presence (H2), and responsiveness (H3) compared to TSEs. These findings exhibit evidence suggesting that the distinct affordances of AIPSEs that are linked to these perceptions – namely the human-like feedback, aggregated content presentation, and increased ability to interpret goals – can be seen as a benefit to individuals when searching in certain contexts. Based on the prior TIME research, these perceptions may also be linked to positive reactions and engagement with AIPSEs (Sundar, 2008), more trust in and/or loyalty toward them (Heckman & Wobbrock, 2000; Sundar, 2004), and increased expectations for these platforms (Sundar, Tamul & Wu, 2014).

Additionally, we predicted that despite these benefits of AIPSEs, TSEs would still have perceived benefits over AIPSEs in certain instances – namely their ability to provide individuals with a variety of information (H4) – which was supported by the results showing that TSEs garner higher perceived variety than AIPSEs. In contrast, our hypothesis suggesting that perceived ease of use would be higher on AIPSEs than TSEs (H5) was not supported, and it was found that perceived ease of use was significantly higher for TSEs than AIPSEs. This is not

entirely surprising given that participants may view their ease of navigating through search engines as a product of prior experience with SEs, and their familiarity with TSEs, rather than a product of interface clutter or the amount of effort needed to find information.

Particularly intriguing patterns emerged for the regression models predicting the likelihood of choosing an AIPSE over a TSE across three different search motivation situations. Overall, the predictive power of the AIPSE-related perceptions was strongest for advice-seeking searches, which showed the highest level of choosing AIPSEs over TSEs among the three search motivation categories. However, for the likelihood of choosing an AIPSE over a TSE in the purchase-related search situations, TSE-related perceptions were more prominent predictors than AIPSE-related perceptions, and even then, the regression model explained only a small portion of the variance in the dependent variable.

Looking at the specific perception variables, perceived social presence of AIPSEs was the strongest positive predictor of choosing an AIPSE over a TSE for advice-seeking searches, followed by perceived coolness of AIPSEs, perceived social presence of TSEs as a negative predictor, perceived responsiveness of AIPSEs as a positive predictor, and perceived variety on TSEs as another negative predictor. This finding suggests that individuals' preference of AIPSEs over TSEs for advice-seeking would likely be most strongly influenced by the social presence and coolness of the search engine technology, along with perceptions about its responsiveness, which makes sense given the act of advice-seeking implies a need for information that is specific to one's request (responsiveness) while also being delivered in an interpersonal way (social presence). For choosing AIPSEs in information-seeking search situations, perceived social presence of AIPSEs was the most prominent positive predictor; yet, perceived ease of using

AIPSEs was also significant, indicating that the social nature of these machines and their ability to succinctly present information may be valued when gathering factual information. Unlike the information-related or advice-seeking situations, for purchase-related search situations, TSE-related perceptions tend to play more significant roles in predicting the likelihood of choosing an AIPSE over TSE, with perceived responsiveness of TSEs being a negative predictor and perceived social presence of TSEs being a positive predictor.

Examining the second research question, dealing with the relationship between hallucination awareness on AIPSE perceptions and likelihood of choosing an AIPSE, the findings were less concrete. Specifically, we were unable to find any significant relationship between any of the AIPSE perceptions or likelihood of choosing an AIPSE and awareness of hallucination, which was surprising given the implications of hallucination on the results one obtains from an AIPSE. Interestingly, over 55% of the participants reported having basic, adequate, or full awareness of AIPSE hallucination, and when asked about their level of concern about hallucination from 1-10 almost 59% reported a level of concern higher than 7. Given this distribution and the nature of hallucination as an issue that can affect the quality of information obtained on AIPSEs, the non-significant relationship between awareness of hallucination and AIPSE perceptions is puzzling, yet positive in terms of potential future adoption rates among individuals who are aware of its shortcomings.

Research questions 3, 4, and 5 examined the relationships between the AIPSE / TSE perceptions and search engine selection (RQ3), average keyword length (RQ4), and link-clicking behavior (RQ5). These relationships were again non-significant, albeit gender being a negative significant predictor of keyword length (i.e., increased keyword length for female, non-binary,

and transgender individuals). A possible explanation for the lack of significant relationships between AIPSE / TSE perceptions and the dependent variables in these models stems from the small sample size of 39 participants from which we were able to connect survey responses to the online search observation data. This is not to say that this sample of 39 participants did not give us a wealth of data in the aggregate; rather, we suggest that future research should strive to reach a sample with larger power to see if these or similar results hold.

The final set of research questions (RQ6, RQ7, and RQ8) provided this study with arguably the most substantial findings, especially in relation to the future of AIPSE use and the potential disruption these platforms may have on traditional paid search engine marketing campaigns. Beginning with RQ6, unsurprising results showed that TSEs were more often used for purchase-related and information-related searches. Conversely, advice-seeking searches were more often conducted on AIPSEs than on TSEs, which makes sense given the abilities of AIPSEs to interpret information or compare options against one another when prompted. As was mentioned in the measurement section, advice-seeking searches include those that have to do with products or services, accounting for the possibility that consumers may come to AIPSEs to weigh the comparative benefits of one brand's products/services over another when coming to a purchase decision. Examples of searches from the online search observation method that would fall into this category include "What brands are best for architectural shingles?," "What is the best dog food for a shetland sheepdog?," "can i get a list of the best budget cruise lines," among others. More targeted research is needed to confirm this kind of relationship, yet these findings pose interesting questions as they relate to consumer behavior on AIPSEs and the potential fit of targeted sponsored advertising on these platforms.

With respect to RQ7, results showed considerable differences in average keyword length between AIPSEs and TSEs, with AIPSE searches using ~7 more keywords on average in each search compared to TSEs. This difference is not only meaningful in terms of providing a more concrete understanding of how users are searching on AIPSEs; these results are relevant for determining the applicability of pay-per-click marketing on AIPSEs. As it stands, fat-head keyword strings (e.g.., "insurance," "dog food") make up millions of monthly searches on TSEs, justifying their relatively high cost to advertisers compared to long-tail keyword strings; within this sample, fat-head keyword strings made up 36.8% of all TSE searches. This is markedly different compared to the way in which keywords seem to be distributed on AIPSEs, where fat-head keyword strings made up only 3.8% of total, thus making traditional SEM keyword buying tactics less compatible on AIPSEs by comparison.

Additionally, t-test results help to showcase (1) differences in average keyword length between different search motivations and (2) provide evidence that suggests SE type and search motivation can affect average keyword length jointly. The results regarding keyword length differences between search motivations demonstrate that queries in each search motivation category require different levels of specificity on average; more specifically, participants tended to be much more elaborative when searching in advice-seeking contexts when compared to information-related or purchase-related contexts. However, when controlling for the type of SE used, differences between information and purchase-related searches ceased to be significant on TSEs and AIPSEs, indicating that the average level of specificity required (i.e., number of words used) in these motivational states may be more similar than initially conveyed by the more parsimonious t-test results (RQ7.2). Exploring the joint effect of SE type and search motivation,

findings indicate that differences in average keyword length within the same motivation category were significant between AIPSEs and TSEs, further demonstrating participants' tendency to elaborate when searching on AIPSEs, regardless of the motivation.

Finally, results from RQ8 demonstrate the differences in clicking behavior between SE types and motivations. First, given the comparative lack of links available to click on within AIPSE results, it is unsurprising that RQ8.1 results show that there were roughly 14 times more clicks resulting from TSE searches (275 vs 19). Results from RQ8.4 echo these findings, showcasing differences in link-clicking behavior within the same motivation between the two different SE types, where TSEs commanded significantly more link-clicks in each comparison group.

Chi-square tests examining the differences in link-clicking behavior between motivations (RQ8.2) revealed that purchase-related searches resulted in significantly higher levels of clicking behavior when compared to both information-related and advice-seeking searches. When investigating link-clicking behavior between search motivations while controlling for SE type (RQ8.3), results showed that both advice-seeking and purchase-related searches resulted in higher levels of clicking behavior than information-related searches on TSEs; yet, purchase-related and advice-seeking searches were not significantly different, which is interesting given the potential for sponsored advertisements to appear in both types of searches. There were no significant differences in any motivation group comparisons of link-clicking behavior within AIPSE.

Looking at behavior within each SE type further, purchase-related searches on TSEs resulted in the highest proportion of clicks (69.2%), followed closely by advice-seeking searches

(66.2%), and then a sizable drop in clicking behavior within information-related searches (51.8%). For AIPSE clicking behavior, purchase-related searches remained the highest proportion (14.3%) despite the low total number of clicks; however, information-related searches resulted in a higher proportion of clicks (13.9%) compared to advice-seeking (9.7%) on AIPSEs. These results must, of course, be taken with caution considering the low number of total AIPSE clicks; yet, they pose interesting implications for the future use of AIPSEs as consumers become more comfortable with engaging with URLs presented on them.

Looking exclusively at the search episode data collected from TSE searches – and specifically at which kind of content was presented to users after a given search, including the navigation bar, application bar, PPC ads (sponsored), organic, and knowledge graph content (see Figure 4) – the presence of each content type after searches of a certain motivation helps to solidify the merit of our categorization scheme. Examining the average number of sponsored options presented after a search under a given motivation, purchase-related searches resulted in much higher numbers of average ads presented ($M = 20.05$; $SD = 41.14$) compared to both advice-seeking ($M = 7.51$; $SD = 24.73$) and information-related searches ($M = 0.3$; $SD = 1.46$). These findings go beyond showcasing the ability of our computational model to sort participant searches into the correct category, as this is the general distribution we would expect to see given the nature of these three types of search motivations; they also help to demonstrate that purchase-related searches are not the only type of search that is of interest to advertisers, in that advice-seeking searches that have to do with products or services are also important to consider, especially given the ways AIPSEs have been shown to be used in this study.

**Theoretical and Practical Implications**

This study's findings offer important implications for future research and practice in the search engine domain and broader digital media environment. First, individuals' perceptions of AIPSEs in connection to this technology's unique affordances tend to be stronger than perceptions of TSEs in terms of perceived coolness, social presence, and responsiveness, which bodes well for the future adoption and widespread use of this new technology. This insight seems to explain the current trend of relatively higher likelihood of choosing AIPSEs over TSEs when seeking advice, as these factors affect the platform's ability to provide this type of answer to consumers. However, as AIPSE capabilities evolve, and more individuals start using this technology for broader search needs, these affordance-related perceptions may shift – influencing individuals' engagement with AIPSEs – which calls for systematic research on AIPSEs and future search behavior on them.

Second, perceived social presence emerged as the most consistent predictor of the likelihood of choosing AIPSEs over TSEs across all three search motivation categories. This is an interesting finding, in that the social nature of AIPSEs is arguably the most unique affordance they offer compared to TSEs. This perception is also not necessarily tied to one affordance alone, but rather a conglomerate – such as the presentation of information, the quickness and cadence of the system in answering queries, and the tone in which information is conveyed, etc. – seemingly making this measure a good indicator of how a collection of features can influence the affordance perceptions of individuals about this new technology as a whole.

Another noteworthy insight is offered for the likelihood of choosing an AIPSE over a TSE in the purchase-related search situations, where TSE-related perceptions were more

prominent predictors than AIPSE-related perceptions. One plausible explanation is a lack of SEM and shopping link options on the current AIPSEs, and the fact that individuals are still predominantly relying on TSEs for purchase-related searches. However, this trend can change as the traditional SEM and search results pages evolve to respond to AI-led searches, and if AIPSEs start implementing advertising options. Given that purchase-related searches are the most directly relevant to search advertising, and of high interest to advertisers, individuals' adoption and engagement with this type of search and individuals' perceptions and attitudes toward new forms of AIPSE advertising require further research to advance our understanding.

In this same vein, online search observation data provides equally important implications for future research and practice in the search engine advertising field. First, TSEs were, of course, used more frequently than AIPSEs in our online observation results; yet, AIPSE searches did make up over a quarter (25.4%) of the total searches conducted. On a larger, everyday scale, increased reliance on AIPSEs could significantly impact the number of searches conducted on Google (or other TSEs), which could then influence the effectiveness of certain sponsored campaigns as a product of less search volume.

In terms of query formulation on each SE, data shows little overlap in the way users form their queries on AIPSEs vs TSEs. Being that AIPSEs had very few fat-head keyword searches, this could suggest that fat-head keyword targeting will not be affected by reliance on AIPSEs, while making long-tail keyword targeting more difficult on TSEs as consumers divide their elaborative searches across these platforms. Overall, if advertisers aim to connect with consumers on AIPSEs in a future capacity – which is likely given its quick adoption and potential to disrupt TSE use – it is likely that new tactics will need to be devised to disseminate

sponsored content that is in line with the way in which they search and the format in which AIPSE content is presented to consumers.

The impact of AIPSEs on the search environment also seems to depend on the motivation of the search being conducted – whether it was information-related, advice-seeking, or purchase-related. If AIPSEs are more often used to conduct information-related and advice-seeking searches – which are less often accompanied by sponsored ads on TSEs – then reliance on AIPSEs may offer a complementary role to TSEs instead of a competitive one. However, if consumers become more comfortable with using AIPSEs to search for information about products or services (in a purchase-related or advice-seeking manner), serious consideration should be given to the development of sponsored ad placement on AIPSEs. This would require large-scale investigations into how consumers form queries on these platforms, along with the development of software that could unobtrusively provide link recommendations to consumers in a way that aligns with the layout and function of AIPSEs, while also maintaining ethical practices for differentiating sponsored content from organic content.

Overall, this exploratory research provides a much needed empirical insight for scholars employing theories such as TIME, MAIN, and uses and gratifications who aim to investigate how the technological affordances of AIPSEs or motivations may affect the way consumers navigate the challenging online search environment. We suggest that this research and resultant findings should be used as a stepping-stone for more targeted research on each of the AIPSE affordances covered in this study, among others, with scholars manipulating interactive aspects of the interface to investigate their influences on consumer perceptions and behaviors. Additionally, this research proves as a useful guide for advertising practitioners as they navigate

this untrodden online territory where their target audience may be utilizing tools they do not know how to leverage yet. We recommend that advertisers begin to familiarize themselves with how these LLM programs work and how consumers may be leveraging them to find information as covered above, adapting their content and targeting strategies accordingly to fit an environment where TSEs and AIPSEs are utilized. This shift may involve focusing more on SEO fine-tuning of websites, as high-quality links seem to be what AIPSEs present to users; or this may require advertisers to investigate the applicability of long-tail or advice-seeking keyword strings with their product offerings, as this seems to be a main way in which AIPSEs are currently utilized.

### Limitations and Suggestions for Future Research

Although these findings are interesting, this study does have limitations in terms of methodology, along with suggestions for future studies to improve upon our learnings. The first limitation that should be addressed is the sample of participants, as our sample was not representative of the general population, and thus the reader needs to take caution in generalizing the findings. We use our findings to suggest trends that may appear in the population, but more representative sampling methods when funds are available would help solidify the merit of the data we provide here.

Additionally, to ensure the quality of our data did not suffer due to the amount of perception variables included, several were left off. Future research should expand upon the measures included in the current study, while also adding other perceptions that may capture further affordance differences between the two types of SEs. For example, including measures

that deal with perceived behavioral control (Wu, 2006) or perceptions about these systems being a “helper” (Sundar, 2008) may reveal other relationships that this study was unable to examine.

Furthermore, we limited our comparison of TSEs and AIPSEs in the online search observation method to Google and Google Bard alone, as we found that creating multiple search observation architectures for each platform was unsustainable and may result in issues comparing each platform to one another (i.e., one platform offers a certain affordance that another does not). While this choice made the collection and comparison of participant behavior more streamlined, our findings are constrained to these two platforms, as it is possible that behaviors and choices may be affected when consumers use different types of TSEs or AIPSEs. More expansive research on the remaining platforms (i.e., Bing Copilot, Perplexity.ai, etc.) is needed to uncover further potential relationships.

While AIPSEs and TSEs are interesting to compare on many levels, differences in the number of links presented – and particularly sponsored links – on each platform's result page make the comparison of clicking behavior difficult given the consistent lack of links or sponsored links. For a more accurate comparison, future research should work to artificially include URL content, including ones labeled as sponsored, into the AIPSE results page to test whether these options are seen as useful to consumers, further investigating the applicability of a search advertising model on AIPSEs.

Finally, given the intrusive nature of recording participants' search behaviors, the use of anonymous emails through Google that participants used to protect their identities, and the complexity of installing a Chrome Extension on one’s browser, this study experienced high levels of drop off from survey response to participation in our online observation. Additionally,

by asking participants to search while not signed into their own Google Chrome account, certain streamlined features may have been unavailable to them, such as password recognition and cookie storage from previous use of certain websites, affecting their web use. Future studies should attempt to simplify this process, or further incentivize participation in the online observation aspect, as research using this type of method will be essential to furthering our understanding of AIPSE use. Despite these limitations, we provide a much-needed base of empirical work for understanding consumers' use of AIPSEs and their potential to disrupt traditional search advertising models. As such, we encourage others to expand on this base in the ways outlined above, among others, furthering our understanding of this emerging phenomenon.

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**APPENDIX A**
**SURVEY QUESTIONNAIRE**

**Survey of Online Search - Generative AI vs Traditional Search Engine**

**Participant Identification**

- Please enter your Prolific ID:
    - _____

**Screening Questions (Any "no" directs participant to end of survey)**

- How old are you?
    - Less than 18 years old → End of survey
    - 18 + years old → Continue
- Do you currently live within the United States?
    - Yes → Continue
    - No → End of survey
- Have you used **BOTH** a traditional search engine (I.e., Google, Bing, Yahoo, etc.) and an AI-powered search engine (Google Bard, Bing Chat, Perplexity.ai, etc.) in the last 3 months?
    - Yes → Continue
    - No → End of survey

**Participant Consent**

- Do you agree to participate in this research?
    - Yes
    - No

**Traditional Search Engine Questions**

Please indicate your prior use of, comfortability with, information vetting process, and content choices while using traditional search engines below.

- How many hours per week do you use traditional search engines (such as Google, Bing, or Yahoo)?
    - Less than 1 hour per week
    - 1-2 hours per week
    - 3-5 hours per week
    - 6-9 hours per week

    - 10+ hours per week
- On a scale of 1-10 (where 1 is not at all comfortable and 10 is extremely comfortable) how comfortable are you with using a traditional search engine to find information online?
    - 1 – 10 scale
- Which traditional search engines have you used?
    - Google
        - Never used it
        - Have used it a few times but don't use it anymore
        - Have used it multiple times but don't use it frequently
        - Use this frequently
        - Use this all the time when I search.
    - Bing
    - Yahoo

- How often do you use traditional search engines for the following purposes?
    - To shop for products or services (e.g., product search, price comparisons, retail outlets, purchasing, etc.)
        - Never
        - Rarely
        - Occasionally
        - Usually
        - Always
    - To search for factual information
    - To seek advice or recommendations
    - To seek news

- The following questions will ask you about your opinions about traditional search engines (not AI-powered ones) and your experience with them. Please rate your agreement with the following statements: (1 = strongly disagree; 7 = strongly agree)
    - Perceived Coolness – (Wang & Sundar, 2018)
        - Traditional search engines are on the cutting edge
            - Strongly disagree
            - Disagree
            - Somewhat disagree
            - Neutral
            - Somewhat agree
            - Agree

            - Strongly agree
        - Traditional search engines are unique
        - It's cool how traditional search engines work
        - Traditional search engines have some cool features
        - If I made a list of cool technology, traditional search engines would be on it
    - Perceived Social Presence – (adapted from Wu's (2006) personalization scale, which was adapted from Short, Williams & Christie's (1976) social presence scale)
        - After using a traditional search engine, I come away feeling like I had a personal conversation
        - After using a traditional search engine, I come away feeling like it talks back to me while I interact with the content.
        - I feel that traditional search engines are sensitive to my needs as I search for information.
        - When using a traditional search engine, I feel the need to phrase my question politely in the search box
            - (added to scale based on findings from Nass & Moon (2002))
    - Perceived Responsiveness – (adapted from Wu (2006) and Sundar & Limperos (2013))
        - Traditional search engines allow me to clarify my question if the first question I asked did not result in my desired outcome
        - Traditional search engines have the ability to respond to my specific questions quickly and efficiently. – (Wu, 2006)
        - Traditional search engines have the ability to respond to my actions on their interface quickly and efficiently – (Wu, 2006)
        - Traditional search engines have the ability to anticipate my needs – (Sundar & Limperos, 2013)
    - Perceived Variety – (Sundar & Limperos, 2013)
        - Traditional search engines allow me to obtain a wide variety of information.
        - Traditional search engines help me to skim and check out various links.
        - Traditional search engines allow me to surf for things that I am interested in.
        - Traditional search engines allow me to browse freely.
    - Perceived Ease of Use – (Wang & Sundar, 2018)
        - Navigating on a traditional search engine is clear and understandable

        - Navigating on a traditional search engine does not require a lot of mental effort
        - Navigating on a traditional search engine is easy

- Please rate the following statements about search results provided by traditional search engines you have used based on the amount you agree or disagree with them.
    - Traditional search engine results provide accurate information
        - Strongly disagree
        - Disagree
        - Somewhat disagree
        - Neutral
        - Somewhat agree
        - Agree
        - Strongly agree
    - Traditional search engine results provide useful information
    - Information in traditional search engine results can be relied on to make important decisions

**AI-Powered Search Engine Questions**

For the purposes of this research, we define AI-powered search engines as platforms which use artificial intelligence to interpret a user's query and generate a response, while also being able to draw on up-to-date information from the World Wide Web to generate these responses (e.g., Google Bard, Bing Chat, Perplexity.ai).

Please indicate your prior use of, comfortability with, information vetting process, and content choices while using AI-powered search engine features below.

- How many hours per week do you use AI-powered search engines (such as Bing Chat, Google Bard or Perplexity.ai)?
    - Less than 1 hour per week
    - 1-2 hours per week
    - 3-5 hours per week
    - 6-9 hours per week
    - 10+ hours per week
- On a scale of 1-10 (where 1 is not at all comfortable and 10 is extremely comfortable) how comfortable are you with using AI-powered search engines to find information online?
    - 1 – 10 scale

- Which AI-powered search engines have you used?
    - Google Bard
        - Never used it
        - Have used it a few times but don't use it anymore
        - Have used it multiple times but don't use it frequently
        - Use this frequently
        - Use this all the time when I search.
    - Bing Chat
    - Perplexity.ai
    - You.com
    - Komo AI
    - Waldo AI]
    - Other
- If "Other" selected above, please specify which AI-powered search engine you have used below.
    - _____

- How often do you use AI-powered search engines for searching or creating the following types of information?
    - To shop for products or services (e.g., product search, price comparisons, retail outlets, purchasing, etc.)
        - Never
        - Rarely
        - Occasionally
        - Usually
        - Always
    - To search for factual information
    - To seek advice or recommendations
    - To seek news

- The following questions will ask you about your opinions about AI-powered search engines (not traditional search engines) and your experience with them. Please rate your agreement with the following statements: (1 = strongly disagree; 7 = strongly agree)
    - Perceived Coolness – (Wang & Sundar, 2018)
        - AI-powered search engines are on the cutting edge
            - Strongly disagree
            - Disagree
            - Somewhat disagree

            - Neutral
            - Somewhat agree
            - Agree
            - Strongly agree
        - AI-powered search engines are unique
        - It's cool how AI-powered search engines work
        - AI-powered search engines have some cool features
        - If I made a list of cool technology, AI-powered search engines would be on it
    - Perceived Social Presence – (adapted from Wu's (2006) personalization scale, which was adapted from Short, Williams & Christie's (1976) social presence scale)
        - After using an AI-powered search engine, I come away feeling like I had a personal conversation
        - After using an AI-powered search engine, I come away feeling like it talks back to me while I interact with the content.
        - I feel that AI-powered search engines are sensitive to my needs as I search for information.
        - When using an AI-powered search engine, I feel the need to phrase my question politely in the search box
            - (added to scale based on findings from Nass & Moon (2002))
    - Perceived Responsiveness – (adapted from Wu (2006) and Sundar & Limperos (2013))
        - AI-powered search engines allow me to clarify my question if the first question I asked did not result in my desired outcome
        - AI-powered search engines have the ability to respond to my specific questions quickly and efficiently. – (Wu, 2006)
        - AI-powered search engines have the ability to respond to my actions on their interface quickly and efficiently – (Wu, 2006)
        - AI-powered search engines have the ability to anticipate my needs – (Sundar & Limperos, 2013)
    - Perceived Variety – (Sundar & Limperos, 2013)
        - AI-powered search engines allow me to obtain a wide variety of information.
        - AI-powered search engines help me to skim and check out various links.
        - AI-powered search engines allow me to surf for things that I am interested in.
        - AI-powered engines allow me to browse freely.

    - Perceived Ease of Use – (Wang & Sundar, 2018)
        - Navigating on a AI-powered search engine is clear and understandable
        - AI-powered on a traditional search engine does not require a lot of mental effort
        - AI-powered on a traditional search engine is easy

- Please rate the following statements about search results provided by AI-powered search engines you have used based on the amount you agree or disagree with them.
    - AI-powered search engine results provide accurate information
        - Strongly disagree
        - Disagree
        - Somewhat disagree
        - Neutral
        - Somewhat agree
        - Agree
        - Strongly agree
    - AI-powered search engine results provide useful information
    - Information in AI-powered search engine results can be relied on to make important decisions

- Attention Check: To show that you are paying attention to the directions in each question, please select "usually" from the following options:
    - Never
    - Rarely
    - Occasionally
    - Usually
    - Always

**Comparative Use**

In this section we ask you to think about when you would use traditional search engines vs AI-powered search engines by comparison and which you would rely on in certain circumstances.

In each of the following search engine use situations, how many out of 10 times you search, would you likely use a traditional search engine vs an AI-powered search engine?

For example, if about 5 out of 10 times you would use a traditional search engine (e.g. Google) and about 5 times you would use an AI-powered search engine, please check the following choice: 5/10 Traditional Search Engine -- 5/10 AI-powered Search Engine

- Suppose you need to search for the best restaurant to eat at with a group of friends on the weekend. How many out of 10 times you search would you likely use each?
    - Purchase (Category not visible to participants)
        - 10/10 Traditional Search Engine -- 0/10 AI-powered Search Engine
        - 9/10 Traditional Search Engine -- 1/10 AI-powered Search Engine
        - 8/10 Traditional Search Engine -- 2/10 AI-powered Search Engine
        - 7/10 Traditional Search Engine -- 3/10 AI-powered Search Engine
        - 6/10 Traditional Search Engine -- 4/10 AI-powered Search Engine
        - 5/10 Traditional Search Engine -- 5/10 AI-powered Search Engine
        - 4/10 Traditional Search Engine -- 6/10 AI-powered Search Engine
        - 3/10 Traditional Search Engine -- 7/10 AI-powered Search Engine
        - 2/10 Traditional Search Engine -- 8/10 AI-powered Search Engine
        - 1/10 Traditional Search Engine -- 9/10 AI-powered Search Engine
        - 0/10 Traditional Search Engine -- 10/10 AI-powered Search Engine
- Suppose you had to answer a question about how many moons each planet in our solar system has. How many out of 10 times you search would you likely use each?
    - Information
- Suppose you wanted to buy a new pair of running shoes. How many out of 10 times you search would you likely use each?
    - Purchase
- Suppose you wanted to know the team names of the last 10 Super Bowl winners, along with who they faced and the end score of the game. How many out of 10 times would you likely use each?
    - Information
- Suppose you had to answer a question about if a certain home goods store carried a tool you need for a project. How many out of 10 times you search would you likely use each?
    - Purchase
- Suppose you had to create a meal plan that is in line with a new diet you are trying out, but don't know what foods to include or how to balance it. How many out of 10 times you search would you likely use each?
    - Advice
- Suppose you had to answer a question about a medical issue that is concerning you before you go see a medical professional. How many out of 10 times you search would you likely use each?
    - Information

- Suppose you had to answer a question about the best clothes to bring on a three week trip to Argentina in May to match typical weather patterns. How many out of 10 times you search would you likely use each?
    - Advice
- Suppose you had to answer a grammatical question about the correct way to phrase a sentence in an email. How many out of 10 times you search would you likely use each?
    - Advice

- How often do you find yourself using traditional search engines since the release of AI-powered search engines?
    - Much less
    - Slightly less
    - No difference
    - Slightly more
    - Much more

**Perception of difference**

- When you think about the search results presented after queries, how different do you feel between traditional search engine results and AI-powered search engine results
    - Extremely similar
    - Mostly similar
    - Somewhat similar but somewhat different
    - Mostly different
    - Extremely different
    - Not sure

- What specific differences stand out to you between traditional search engine results and AI-powered search engine results? Please describe all the differences you notice, separating each difference with a comma
    - Open answer: _____
    - Added skip functionality on “1” and “9” to make sure people who answer that there are not differences are taken to the next question

**Search Engine Advertising**

The following questions ask your opinions about search advertising (sponsored or paid listings on search engine results) in general. These questions are NOT about any particular ads.

- Please rate the following statements about search advertising in general on the following attributes based on the amount you agree or disagree with the statement.
    - Awareness/knowledge of search ads
        - I know how search ads are placed on search engines
            - Strongly disagree
            - Disagree
            - Somewhat disagree
            - Neutral
            - Somewhat agree
            - Agree
            - Strongly agree
        - I know why certain ads are higher up on search engines than other ads
        - I know how search engines make money off of pay-per-click ads
        - I know the difference between different types of search ads like pay-per-click ads and display ads
    - Ad avoidance (Guardia, 2015)
        - I do not pay attention to pay-per-click or display ads
        - I go out of my way to avoid clicking on or engaging with search ads
- Please rate the following statements about search advertising on traditional search engines on the following attributes based on the amount you agree or disagree with the statement.
    - Perceived utility of traditional search engine ads (Pollay & Mittal, 1993)
        - Search ads on traditional search engines help raise our standard of living
            - Strongly disagree
            - Disagree
            - Somewhat disagree
            - Neutral
            - Somewhat agree
            - Agree
            - Strongly agree
        - Search ads on traditional search engines result in better products for the public
        - Search ads on traditional search engines tell me what people with lifestyles similar to mine are buying and using
        - Search ads on traditional search engines help tell me which brands have the features I am looking for
        - Search ads on traditional search engines are essential
    - Attitudes towards traditional search engine ads (Pollay & Mittal, 1993)

        - Search ads on traditional search engines promote undesirable values in our society
        - Search ads on traditional search engines are a valuable source of information about products/services
        - I consider search ads on traditional search engines unwelcome interruption
        - Search ads on traditional search engines are not an important issue for me, and I am not bothered by them
        - Overall, I like search ads on traditional search engines
- **The following are hypothetical statements. Search advertising does not currently exist on AI-powered search engines** Please rate the following hypothetical statements about search advertising on AI-powered search engines on the following attributes based on the amount you would agree or disagree with the statement.
    - Perceived utility of hypothetical AI-powered search engine ads (Pollay & Mittal, 1993)
        - Search ads on AI-powered search engines would help raise our standard of living
            - Strongly disagree
            - Disagree
            - Somewhat disagree
            - Neutral
            - Somewhat agree
            - Agree
            - Strongly agree
        - Search ads on AI-powered search engines would result in better products for the public
        - Search ads on AI-powered search engines would tell me what people with lifestyles similar to mine are buying and using
        - Search ads on AI-powered search engines would help tell me which brands have the features I am looking for
        - Search ads on AI-powered search engines would be essential if implemented
    - Attitudes towards hypothetical AI-powered search engine ads (Pollay & Mittal, 1993)
        - Search ads on AI-powered search engines would promote undesirable values in our society
        - Search ads on AI-powered search engines would be a valuable source of information about products/services

        - I would consider search ads on AI-powered search engines unwelcome interruption
        - Search ads on AI-powered search engines would not be an important issue for me, and I would not be bothered by them
        - Overall, I would like search ads on AI-powered search engines]"

**AI Powered Search Engine Responses**

The following questions are specifically about what you think and do when you see results generated by an AI-powered search engine.

- After receiving information from an AI-powered search engine how often do you engage in the following actions?
    - Double checking the information accuracy on a traditional search engine
        - Never
        - Rarely
        - Occasionally
        - Usually
        - Always
    - Double checking the information accuracy by asking family, friends or experts about the results
    - Navigate to websites provided by the AI-powered search engine in its response
- Are you aware of AI-powered search engine's ability to hallucinate, or fabricate information entirely?
    - No awareness
    - Minimal awareness
    - Basic awareness
    - Adequate awareness
    - Full awareness
- On a scale from 1 to 10 (where 1 is not concerned at all and 10 is extremely concerned), how concerned are you about AI-powered search engines' ability to hallucinate information after a search?
    - 1 – 10 scale

**Demographics**

Please indicate demographic information below.

- How old are you? (please enter your age in years below)

    - _____
- What is your gender? (please select the gender you identify with most closely)
    - Male
    - Female
    - Transgender
    - Non-binary
- What is your race/ethnicity? (please select all that apply)
    - White
    - Hispanic or Latino
    - Black or African American
    - Asian
    - American Indian or Alaska Native
    - Middle Eastern
    - Native Hawaiian or other Pacific Islander
- What is the highest level of education you have completed?
    - Less than high school graduate
    - High school graduate or equivalent
    - Some college, no degree
    - Associate's degree
    - Bachelor's degree
    - Master's degree
    - Doctoral degree
- Are you currently employed?
    - Retired
    - Unemployed
    - Self-employment
    - Part-time employment
    - Full-time employment
- What is your household income?
    - Less than $14,999
    - $15,000 to $19,999
    - $20,000 to $34,999
    - $35,000 to $49,999
    - $50,000 to $74,999
    - $75,000 to $99,999
    - $100,000 to $199,999
    - $200,000 or more

**End of Survey**
Use of responses: please indicate if you would like your responses to be recorded and used in this study.

- If you select "Yes" your data will be stored. If you select "No" your data will be thrown out.
    - Yes
    - No

**Online Observation**
Would you like to participate in a second part of this study within the next 12 hours?

This second part will involve you searching for 1 day (24 hours) through a web hub this research team has developed through Google Chrome. You will be paid $1 for completing our onboarding process and another $4 for searching through an anonymous web hub exclusively for one day.

If you are not interested, and would like to conclude your participation in this research here, please press “No” below. If you are interested and would like to learn more, press “Yes” below.

NOTE: This is not an official consent to participate in the study, but merely an indication of your interest to learn more. If you check yes, you will be contacted by a study team member through the Prolific "Messages" portal.

- Would you like to participate?
    - Yes
    - No

**APPENDIX B**
**ONLINE WEB OBSERVATION MATERIALS**

**Message to Participant After Interest Indicated**
Hello participant. Thank you for indicating your interest in learning more about a second part of our study. We are thrilled to offer you a spot in this aspect of the research.

As indicated in the message, our study will involve you searching for one day through a web hub this research team has developed through Google Chrome. You will be paid $1 for completing our onboarding process and another $4 for searching through an anonymous web hub exclusively for one day (24 hours) in the form of a "bonus payment" from the previous survey study.

We ensure your anonymity and personal data by having you log into Gmail accounts created specifically for this study. This study and chrome extension were approved by the IRB of the University of Minnesota-Twin Cities. To learn more, and to register for this study, please visit the following link **(HYPERLINK)** to our informed consent form and indicate your willingness to participate. Please read it thoroughly, as it has important information about your participation. Thank you!

Please note that we require that you respond to our informed consent in 24 hours from this message to take part in this study. We look forward to hearing from you!

**Message After Consent Obtained**
Thank you for agreeing to participate in this study! We appreciate your willingness to help further the collective knowledge and research within this area.

Pasted below are your unique email address and password that you will use over the next 24 hours. These credentials should be used for BOTH logging into Google and logging into our Web Hub page. You must use a computer for this study.

The directions within our onboarding materials (https://sites.google.com/umn.edu/studyofonlinesearch/home) and the accompanying video will show you how to use these credentials and the steps in which to do them. To complete the onboarding you must login to gmail and the web hub successfully.

Once you have completed the 24 hour period, a popup will appear on the search hub to complete our offboarding materials (https://sites.google.com/umn.edu/study-of-online-search/home), listing your Prolific ID and confirmation of completion, after which we will compensate you via

the Prolific as a “Bonus Payment.” You will be paid $1 for completing the onboarding process (logging into gmail and our web hub successfully), and the remaining $4 for searching for the 24 hour period.

Please note that Google's login system may ask you to verify your login with a phone number. You will not have to do this. If you see this message (shown in step 2 of the onboarding), contact the study team via Prolific and we will disable this Google security feature. To avoid this entirely, please try to log into the Gmail account within 1 hour of this message.

As always, if you have any questions, please do not hesitate to reach out to the team through this Prolific portal or via email (garlo030@umn.edu) for troubleshooting help.

Username: XXXXX@minncal.net
Password: XXXXXXXXXX

**Onboarding Website and Video**
Link to onboarding website: https://sites.google.com/umn.edu/studyofonlinesearch/home

Link to onboarding video:
https://drive.google.com/file/d/1ke3ek2VMgWrOvHuaudIBB_lPuxfuvdLd/view?usp=drive_link