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How does online visual search compare to online textual search when performed using a hedonic or a utilitarian motivation.

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RENOUVELLEMENT DE L'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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CERTIFICAT D'APPROBATION ÉTHIQUE

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Résumé

L'action de chercher et de trouver est un comportement instinctif. C'est en cherchant et en trouvant que les besoins à différents niveaux sont comblés, de la survie à l'épanouissement. L'action de chercher peut se faire en personne ou en ligne. Dans cette recherche, nous avons décidé d'étudier les processus de recherche en ligne. Plus particulièrement, nous voulions comparer la recherche visuelle à la recherche textuelle lorsqu'elles sont combinées avec des motivations hédoniques ou utilitaires et d'en mesurer les impacts sur l'effort cognitif et les émotions.

Notre question de recherche est la suivante : Comment l'expérience de magasinage en ligne initiée par une recherche textuelle se compare-t-elle à l'expérience de magasinage initiée par une recherche visuelle ?

Pour notre expérience, nous avons recrutés 33 participants, et avons utilisé un design intra-sujets avec mesures répétées. Chaque participant a été assigné à deux conditions randomisées comprenant chacune quatre tâches de recherche en ligne. Le sujet de leur recherche était la rénovation d'une cuisine. Les tâches ont été administrées et comptabilisées sur la plateforme de sondage Qualtrics. À la fin de chaque tâche, les participants se sont évalués sur l'échelle SAM (*Self-Assessment Manikin*), nous procurant des données quantitatives. Un court entretien avec le participants s'est tenu afin d'échanger sur leur expérience globale et recueillir des données qualitatives.

L'analyse post-expérimentale a révélée que la recherche visuelle n'était pas fiable pour une motivation hédonique, contrairement à notre hypothèse initiale. En fait, la recherche visuelle était mieux adaptée pour la motivation utilitaire. À l'inverse, les participants ont préféré la recherche textuelle, car elle permettait une plus grande liberté pour une recherche exploratoire hédonique.

Les conclusions de cette recherche sont significatives et mettent en évidence les difficultés de la recherche et de la découverte en ligne. La faible utilité de la recherche visuelle dans sa forme actuelle a le potentiel d'être transformé par l'intelligence artificielle générative (IAG) en priorisant les besoins et mode cognitif des utilisateurs pour chercher et trouver.

Mots clés : recherche visuelle, recherche textuelle, recherche par image, hédonique, utilitaire, cognition, formulation de requête, expérience utilisateur, plaisir, excitation, dominance

Abstract

The act of searching and finding is an instinctual animal behavior. It is through searching and finding that our needs are fulfilled on different levels from survival to thrival. This activity can be practiced in-person or online. For our purposes, we studied the process of searching and finding online. Specifically, we wanted to compare two search methods: textual and visual search, and measure how they affect cognition and emotion when paired with two different types of motivation: utilitarian and hedonic.

Our research question states: How does the experience of shopping online using textual search compare to the one of using visual search?

To execute the study, we deployed a 2 x 2 within-subjects experimental design, with 33 participants. Each participant was assigned two separate randomized sets of four online search tasks. The context was for a kitchen renovation project. The tasks were administered and processed on the Qualtrics survey platform. After each task, a Self-Assessment Manikin (SAM) scale was used to measure and collect the qualitative data, and at the end of the experiment, a post-experiment interview was conducted.

The post-experiment analysis of the quantitative and the qualitative data revealed that contrary to what we hypothesized, visual search was not adequate for hedonic searching. Visual search was better suited for utilitarian searches. Conversely, participants were more partial to textual search for the exploratory searches, as it allowed greater freedom to choose hedonically motivated objects.

The implications of this study are significant at this moment in time, and highlight the pain points of searching and finding online, in particular with visual search. Generative AI has the potential to transform the way visual searches are done. It offers the promise to enhance the user experience by prioritizing needs and cognitive modes of searching and finding.

Keywords: visual search, textual search, image search, hedonic, utilitarian, cognition, query formulation, user experience, valence, arousal, dominance

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List of abbreviations and acronyms

AI	Artificial intelligence
ANOVA	Analysis of variance
CBIR	Content-Based Image Retrieval
HCI	Human-Computer Interaction
GenAI	Generative AI
GPT	Generative Pre-trained
HTML	Hyper Text Markup Language
IAG	l'intelligence artificielle générative
AIME	Amount of Mental Effort
LLM	Large Language Models
SAM	Self-Assessment Manikin
SERP	Search Engine Results Page
UX	User Experience

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As they say, we stand on the shoulders of giants, you are my giants.

My family who patiently and lovingly supported my decision to return and further my studies was exceptional. Your encouragement allowed me to embark on this journey to renew my love of learning.

Finally, I am grateful for the new friendships made at HEC, and my study buddies who helped me push forward by guiding me. I am also grateful to the staff at HEC, you've created a robust learning environment. Also, I would like to thank Michel Keoula, your contributions were essential and your patience in teaching me was greatly appreciated.

Chapter 1 Introduction

The activity of shopping in person is very different than the activity of shopping online. The physicality of being outside the house, in a different environment, stimulates multiple senses simultaneously. The environment is designed to inspire and give ideas, it allows touching, feeling, and assessing products to judge their quality.

In 2024, shopping is an activity practiced both in person and online, both activities are however not experienced in the same way. There is a clear difference in a shopper's experience when stepping inside a store from shopping in front of their computer: open the search engine, type the words that best signify what is looked for and bingo, there are results. However, when the exact words (or keywords, which are trickier) are lacking, the internet might stay opaque. Other ways must be found to search. An individual can type in many iterations to finally come close to describing what the search is for.

Online search relies heavily on text because it is through tags and metatags that searches and discoveries are done. They are the building blocks of the internet, similar to labels or keywords used to classify and describe elements. The tags and metatags make the web discoverable by the search engine's bots, hence, facilitating online searching. These protocols are still in use today (Spinello, 2002).

Initially, the internet was developed by and for the army to decentralize communication systems, as a safeguard from potential enemies (Lukasik, 2011). Subsequently, the network was shared with universities and was further developed and rendered more accessible. The internet has come a long way since, it has become a powerful searching tool used for more than searching for information, one among many, is shopping.

We are currently observing a rise in the usage of LLMs (Large Language Models) by Generative AI, to perform online searches instead of Google searches. This new experiment will not only affect the search activity, it will change and flip the playbook on how searches are computed. It is the right time to ask questions and shape this tool to better serve our needs, and improve the user experience. In this transition away from Google's search algorithms as we have known them (Hart & Staff, 2024).

Currently, if a person is lacking a keyword and decides to do a visual search online for a cereal box for instance, it would involve uploading a picture of the cereal box and the search engine would perform a reverse image search. The results page would show different retailers at different price points. Searching online textually, for that same cereal box, not knowing the name of it, would involve some head scratching. A breakdown of the description, its ingredients, or the nutritional components in the search could become long and puzzling. Fingers would be crossed, with the hope that the search engine would "figure it out". Textual search is useful when the keywords to input in the search bar are known. However, if a person does not have the name, yet has the item in front of them, visual search can be a promising option to consider. It has the potential to find the right items faster and could be easier than the usual textual search.

The focus of this master's in UX (user experience) thesis is on online searching in a shopping context. Shopping is a particular kind of search activity that is extremely reliant on visual information. Adding visuals has significant effects on the quality of messaging, the credibility of the product, the interest, and purchase intentions (Lin et al., 2012). A visual representation allows the discernment of features such as color, texture, shape, size, depth, and much more. The brain identifies images within 13 milliseconds (Potter et al., 2014). A processing time that is 60,000 times faster than text. It is with the eyes that 80% of the information is received (Hill, 2003). Although shopping calls upon multiple senses, it is primarily done with the eyes. It is surprising that nowadays shopping online cannot be done through visual prompts, without heavily relying on textual searches. From a UX point of view, this question reflects how senses are used to go through the shopping process. Before the current search technology can be revisited and improved to allow for greater visual processing on the shopper's part, it is useful to fully grasp what is at play when individual shops on or offline. Let's dive in a bit further.

In 2006, Google introduced the image pack on the results page. They were sets of images taken from various sources from Google's index (B. Oliveira & Teixeira Lopes, 2023). The image results complemented the textual search results and brought richness to the platform. The presentation on the page gradually evolved from a block of thumbnail-sized images to a bar of image categories, up until 2019, when it evolved into a carousel of images.

Visual search matters since the brain is wired to remember images more easily. People think in images, not words (Hill, 2003). A memory of a visual is sometimes more easily transposable into a shape, a finish, or a color, in the search reference. The characteristics of an object are communicated visually. Many online stores have a presence on popular social apps to promote their products, to build up their brand, by using imagery to attract followers. Online imagery in general exploded in recent years, and apps such as Instagram, added filters to make images more alluring and appealing. The presence of visuals facilitates representations of the abstract, it assures that what a person is searching for is what that person finds. What if online shopping could be more pleasant than in-person shopping? What would online shopping look like when done with a visual reference? How is cognition impacted when one lacks the right terminology for a textual search? Taking all these factors into account we formulated our research question.

Research Question

Q: How does the experience of shopping online using textual search compare to that of using visual search?

All shopping is not equal

There is more than one impetus for shopping. As such, the shopping activity can have many purposes, at times it is done by necessity, and at other times it is done by indulgence. There is shopping for essentials such as groceries, shopping for special occasions such as Christmas gifts, for occasional items such as a car, or for something that is a pure frill, like a cool pair of sneakers. The strategy for each purchase is executed differently (Almquist et al., 2016; Li & Xie, 2020).

Shopping for groceries is an essential activity, done regularly. Both utilitarian and hedonic motivations are involved. When picking up some food items, the act is automatic, such as when buying bread or milk. For other items, the shopping can be exploratory, for instance, to provide cooking ideas. A completely different type of shopping example would be shopping for a car. Many factors influence car shopping, an important one is motivation. The spectrum of reasons for getting a car can range from sheer necessity to pure indulgence. Shopping for a vehicle starts before setting foot inside a dealership. The nature of the item requires time; beginning by establishing a checklist of the non-negotiable features, considering specific features such as the horsepower, gas mileage, and other performance metrics (Dasgupta et al., 2022). The car companies present the technical and the visual features side by side on their websites. While an individual reads up on specs, that person is also exposed to the different car models, colors, and features. When enough information is gathered, the next step is to visit the car dealership. A test drive allows an assessment of the feel, the drive, and the design of the car. The back and forth that ensues between the needs, the wants, and the price makes one pause and evaluate the checklist. A balance is sought between the physical look of the car, how the driver feels while driving it, the performance, and the budget. In the end, the selection is based on the model that best fulfills the most needs, while procuring joy in the drive.

Cars and groceries call for two very different kinds of in-person shopping scenarios. Both have in common a motivation that is utilitarian at times and hedonic at other times.

Shopping hedonically is meant to be leisurely and pleasurable, an opportunity to try new things. It pairs well with visual shopping because the aesthetic appeal is appreciated visually (Ryu & Ryu, 2021). On the other hand, a utilitarian shopping motivation is purposeful and goal-oriented. Both motivations: hedonic and utilitarian can be searched by text or with a visual.

An example of hedonically motivated shopping could be a weekly ritual of eating freshly baked croissants from a neighborhood bakery. One would start by taking a pleasant walk towards the bakery, taking in all the smells, as one gets closer and closer to the pastry shop. The anticipation of the buttery taste, the light flaky texture, and the warmth in the mouth while taking the first bite, would have one salivating even before entering the shop The whole event leading up to tasting the actual croissant would count as a pleasurable and positive hedonic shopping experience. There are times, when those associations could be transposed to another product, that produces similar pleasurable moments, such as with cinnamon buns. The similar product category, the cinnamony smells, would be transposed to build up a similar positive savoring experience based on their visual similarities (Piqueras-Fiszman & Spence, 2015). An example of a search motivated by a utilitarian purpose would be purchasing over-the-counter flu medicine ahead of the flu season.

The cereal box, like croissants or milk, can be purchased through hedonic or utilitarian motivation and needs. This begs the question if hedonic and utilitarian motivations can influence the experience of using a visual or textual search method.

Chapter 2 Literature Review

The search for articles on visual search led to topics around online image search, and the many factors shaping it. Examining these elements allowed a better understanding of their current state. It would be logical to start with the history of search engines, what was their initial purpose, and how they evolved into the tools that are used today. This is therefore what the first section is about whereas the second section is about textual search, the default method for online searching. The third section examines the rise of visual searches and the impact online shopping had on user behavior in e-commerce. The fourth section differentiates between the two types of motivators (utilitarian and hedonic) used in this study.

The databases used were ACM Digital and EEE Xplore, for information technologies in visual searches, ScienceDirect (Elsevier) for the cognitive and emotional aspects, and Wiley Online Library for articles related to most of the keywords. (Table 1)

Section	# articles read	# articles retained	Criteria	
			Inclusion	Exclusion
Shaping of Search Engines	Abualsaud & Smucker, 2022 Brin & Page, 2012 Dave, 2013 Deepak and Priyadarshini, 2018 Jansen et al., n.d. Kumar et al., 2017 Mirtaheri et al., 2013 Naughton, 2015 Oliveira, 2021 Oliveira & Teixeira Lopes, 2023 Sanderson & Croft, 2012 Seymour et al., 2011 Spinello, 2002 Trupti et al., 2014	Abualsaud & Smucker, 2022 Brin & Page, 2012 Dave, 2013 Jansen et al., n.d. Naughton, 2015 Oliveira, 2021 Oliveira & Teixeira Lopes, 2023 Sanderson & Croft, 2012 Seymour et al., 2011 Spinello, 2002	Studies on the evolution and history of search engines, from early internet tools (like Arpanet and Yahoo) to modern-day search engines. Research on search engine algorithms, including technologies like web crawlers, metacrawlers, and PageRank. Studies focusing on the impact of search engine innovations, such as backlinks, auto-completion, and spell-check tools in enhancing user experience. Papers that explore the role of content categorization in search engines, especially those related to search result ranking and relevance.	Research not related to online search engines, such as papers focused on offline search behaviors or non-digital environments. Studies that focus exclusively on technical aspects of search engines (e.g., without discussing user interaction, UX, or motivations). Older studies that provide historical context but lack relevance to modern search engine technologies (published before 2000).
keywords	history of search engines, Arpanet, search engine algorithms, web crawlers, metacrawlers, PageRank search engines, backlinks, auto-completion, spell-check, categorization, search result ranking			
Frustrating Textual Searches	Aula et al., 2010 Barifah & Landoni, 2020 Chevalier et al., 2014 Medlar et al., 2021 Pirolli, 2009 Poddar and Ruthven, 2010 Rieh et al., 2012 Vanderschantz et al., 2014 Yang et al., 2018	Aula et al., 2010 Barifah & Landoni, 2020 Chevalier et al., 2014 Medlar et al., 2021 Pirolli, 2009 Poddar and Ruthven, 2010 (Rieh et al., 2012 (Yang et al., 2018)	Studies that analyze frustrations experienced during textual search, including issues like irrelevant results, cognitive load, and search fatigue. Research on the mental effort required in textual search, such as the Amount of Mental Effort (AIME) model and how search difficulty impacts usability and satisfaction (e.g., through increased anxiety or task complexity). Articles discussing user frustrations with textual search strategies, including auto-completion, term suggestion, and term correction. Research that examines the impact of search term formulation difficulties and the cost-benefit trade-offs in textual search (e.g., Information Foraging Theory).	Studies focusing on non-textual or visual search, which do not address text-based search frustration specifically. Research that focuses solely on search algorithm optimization without considering the user experience and cognitive aspects of textual searches. Studies that do not evaluate user frustration or emotional responses during textual search tasks.
keywords	textual search, irrelevant search results, search with no search word, cognitive load, AIME, mental load, usability, user-satisfaction in online search, frustrating textual search, auto-completion tools, auto-correct tools, search term formulation, Information Foraging Theory			

Section	# articles read	# articles retained	Criteria	
			Inclusion	Exclusion
Visual Search Gaining Ground	Barthel et al., 2022 Calleja and Willoughby, 2023 Chang et al., 2023 Dagan et al., 2023 Eswaran & E, 2022 Flavián-Blanco et al., 2011 Gu et al., 2021 Lasserre et al., 2019 Lei et al., 2023 Luo et al., 2020 Misra et al., 2023 Novela et al., 2020 Poor et al., 2022 Shao et al., 2019 Sumarliah et al., 2022) Togashi and Sakai, 2020 Wu et al., 2019 Yang et al., 2017 Yang et al., 2018 Zhao et al., 2020 Barthel et al., 2022 Calleja and Willoughby, 2023 Barthel et al., 2022 Calleja and Willoughby, 2023 Chang et al., 2023 Dagan et al., 2023 Eswaran & E, 2022 Flavián-Blanco et al., 2011 Gu et al., 2021 Lasserre et al., 2019 Lei et al., 2023 Luo et al., 2020 Misra et al., 2023 Novela et al., 2020 Poor et al., 2022 Shao et al., 2019 Sumarliah et al., 2022) Togashi and Sakai, 2020 Wu et al., 2019 Yang et al., 2017 Yang et al., 2018 Zhao et al., 2020	Eswaran & E, 2022 Flavián-Blanco et al., 2011 Lasserre et al., 2019 Eswaran & E, 2022 Flavián-Blanco et al., 2011 Eswaran & E, 2022 Flavián-Blanco et al., 2011 Lasserre et al., 2019	Studies on visual search technologies, especially those exploring image-based search methods (e.g., uploading images for search results). Research examining the evolution of visual search tools, particularly in mobile devices and e-commerce, and how they have become integral in shopping experiences. Articles that explore the emotional and cognitive impact of visual search on users, such as how visual stimuli can enhance engagement or alter behavior. Studies that look into the integration of visual search with AI-driven tools and how it enhances search efficiency and personalization.	Research that focuses solely on image retrieval technologies without relating them to user search experiences or behavioral outcomes. Studies that do not consider the cognitive or emotional dimensions of visual search (e.g., focusing only on image classification or indexing without regard to the user's mental processes). Articles that exclusively cover offline visual search practices (e.g., in physical stores) and do not address online visual search behaviors.
keywords	visual search, visual search technologies, image-based search methods, CBIR, content-based information retrieval, cognition in visual search, visual search in AI			

Section	# articles read	# articles retained	Criteria	
			Inclusion	Exclusion
Hedonic and Utilitarian Motivation Effects	Berget & Sandnes, 2019 Babin et al., 1994 Chung & Tan, 2004 Daugherty et al., 2008 Davis, 1989 Gupta & Mukherjee, 2022 Hirschman & Holbrook, 1982 Hung et al., 2021 H. Wu. et al., 2023 Lee & Kim, 2018 Liu et al., 2024 Nieuwenhuysen, 2018 Novak et al., 2000 Rieh et al., 2012 Schnurr & Wetzels, 2020 Setiawan et al., 2020 Sumarliah et al., 2022 Vanderschantz et al., 2014 W.-Y. Wu et al., 2018 Widagdo & Roz, 2021 Wilson, 1999 Wu. et al., 2023 Zhao et al., 2016	Berget & Sandnes, 2019 Babin et al., 1994 Chung & Tan, 2004 Daugherty et al., 2008 Davis, 1989 Gupta & Mukherjee, 2022 Hirschman & Holbrook, 1982 Hung et al., 2021 H. Wu. et al., 2023 Lee & Kim, 2018 Nieuwenhuysen, 2018 Novak et al., 2000 Rieh et al., 2012 Schnurr & Wetzels, 2020 Setiawan et al., 2020 Sumarliah et al., 2022 Vanderschantz et al., 2014 W.-Y. Wu et al., 2018 Widagdo & Roz, 2021 Wilson, 1999 Wu. et al., 2023 Zhao et al., 2016	Studies exploring the distinction between hedonic and utilitarian motivations in online shopping, particularly how these motivations affect search behavior. Research that examines emotional responses, cognitive load, and user experience during online searches under hedonic vs. utilitarian motivations. Literature that investigates how hedonic shopping (seeking pleasure, exploration) and utilitarian shopping (focused on goals, and efficiency) influence search strategies and search modality preferences (visual vs. textual). Articles that focus on the psychological effects of hedonic and utilitarian motivations in e-commerce and search behavior (e.g., arousal, valence, dominance).	Studies that focus purely on shopping behaviors without addressing search behaviors or search modalities. Research on hedonic and utilitarian motivations that are not related to online shopping or search (e.g., studies on consumer behavior in physical stores). Articles that discuss search behaviors but do not consider the interaction between motivation and search modality (visual vs. textual).
keywords	Hedonic, utilitarian, cognitive load, user experience in online searches, hedonic vs. utilitarian search motivations, hedonic shopping, utilitarian shopping, online search strategies, e-commerce			

Table 1 - Literature Review Methodology

1. Shaping of Search Engines

The information needs keep growing, and are more and more complex, the expectation is that the search results should be instantaneous, properly ranked, and relevant (Abualsaud & Smucker, 2022).

Before the internet was available to all, there was Arpanet. This network was created for and by the army to facilitate communication among different channels in the military. The type of searches done was for information and definitions. Later, the access was shared with universities who also searched for information for research and learning purposes. With the universities came further development of the search tools. Search engines have been part of the digital landscape for over thirty years. Web crawlers were and still are the default method used by search engines to "go in search of information." These small programs or bots wandered the web, gathering (crawling) data, downloading documents by following links that needed to be explored, from search requests, refreshing content, or following links with related content from other links (Udapure et al., 2014). The bots gathered data for indexing, storing, and facilitating quick searches. In addition, metacrawlers were also bots that crawled multiple search engines and filtered for duplicates (Seymour et al., 2011).

Metatags were written in HTML in the backend code of a website. They contained keywords of the website or page, providing descriptions with summaries of the site, to be searched by crawlers (Spinello, 2002). The manner to search on the internet was pre-determined, words had to be entered to start any type of search. This explains why individuals are programmed to perform a search with search words, this is the primary method that has been taught (Sanderson & Croft, 2012).

Yahoo's approach to information was innovative, they organized content for their users with the end goal of offering an online user experience. They achieved this by offering a "human-curated directory of websites" (Naughton, 2015). "Content managers" were in charge of curating content, creating menus, and categories they believed would interest and be relevant to users. The crawling technology was used internally for research purposes. Yahoo was known as the "cool web", setting trends, as influencers do today. They wanted to stand out, by providing searchers with trendy topics. According to Yahoo, categories and classifications were the basis of the individual's worldview (Naughton, 2015). AskJeeves had a similar philosophy, as it developed the ability to extract important words in a query to figure out the user's intent and offer relevant results (Seymour et al., 2011).

It is worth noting that AltaVista, one of the most effective search engines at the time, had machines with such processing power that they could crawl and re-crawl repeatedly, to make the full content of a website searchable and fresh (Mirtaheri et al., n.d.). In addition, AltaVista had a built-in mechanism for image search having indexed approximately ten million images on the web, in 1999 (Jansen et al., n.d.).

Google, innovated by adding boolean operators, correcting spelling errors, auto-completing the search, and suggesting queries, all tools that are still used to this day to facilitate searches

(B. Oliveira & Teixeira Lopes, 2023); (Seymour et al., 2011). The thing that set Google apart from the pack was "backlinks" (Brin & Page, 2012). A backlink is a link on another website that points back to your website. As the number of backlinks increases so does a website's popularity and ranking on Google (Dave, 2013). An analogy to explain backlinks is academic citations: the idea that the number of times an article is cited increases its reliability and its quality. Consequently, it will be ranked higher and receive greater exposure. Using the same principles, the PageRank formula enables Google to offer a greater level of relevance ranking (B. E. Oliveira, 2021).

2. Frustrating Textual Searches

From the beginning, online search was done using words and it has remained this way for a good 30 years. Textual search is a practice that is well embedded in daily habits, and as mentioned earlier, it is the primary way a search is started. As in the "Theory of optimal foraging" where it is in an animal's nature to try and spend the least amount of energy to find an optimal food source (Pirolli, 2009), it seems to be in human's nature to try to find information with the least amount of effort (Yang et al., 2018). This becomes "The Information foraging theory" (Pirolli, 2009): the cost-benefit interaction equivalent to the human-computer interaction (HCI). In textual searches, text-based strategies include term suggestion, auto-completion, and term correction among others. These tactics were developed to help a searcher find information in a time-efficient way. Nevertheless, there are instances when the search is difficult to verbalize. The mental effort necessary to formulate a concept or a complex idea increases the occurrence of irrelevant results, which in turn significantly and negatively affects usability and satisfaction levels (Chevalier et al., 2014). The Amount of Mental Effort (AIME) invested in online searching influences user experience, and when a search necessitates greater effort, the whole experience becomes frustrating and increases levels of anxiety (Rieh et al., 2012). (Poddar & Ruthven, 2010) identified task complexity as responsible for lowering positive emotions and mounting uncertainty during the whole search process (Barifah & Landoni, 2020).

As frustrations grow, the search approach affects the time spent on searching. The evaluation of the results is exhaustive, the user scrolls up and down the results page randomly with no intent on reading the page contents. The search process becomes desperate as the user revisits previously viewed pages (Aula et al., 2010). These actions are dynamic and consequential, having a direct impact on cognition relative to the search difficulty. To alleviate some of the frustration, search engines have built-in tools to ease textual search and they intuitively complete the search box words or auto-correct spelling mistakes (Medlar et al., 2021).

3. Visual Search Gaining Ground

A common practice in shopping for clothing is to perform searches on smartphones simply by taking a quick picture on a mobile device and uploading it onto a search engine. There's an expectation of getting relevant results, (Eswaran & E, 2022) replacing the physicality of browsing shop displays (Lasserre et al., 2019). An image not only offers the look and shape of an object, it allows for an assessment of the texture and the feel of an object, stimulating the tactile senses. When a visual search is performed, the emotional state in the pre-search process is primed with motivation, it influences behavior and attitudes (Flavián-Blanco et al., 2011). The presence of images on the web gradually increased with their usage on social media apps. Users wanting to share their hobbies or interests with beautiful "lifestyle" pics, could access the built-in filters which allowed the modification of images to make them more appealing. It allowed one to share and make visible one's presence online with some sharing their foodie passion, and others sharing their fashion style. A new wave of self-expression was born, that enabled monetization by engaging followers (Lasserre et al., 2019).

4. Hedonic and Utilitarian Motivation Effects

Studies on motivation during online shopping have increased during and after the COVID-19 pandemic. The confinement shifted in-person shopping to online shopping, (Sumarliah et al., 2022) and what became prevalent during the pandemic is here to stay. The pandemic generated a lot of negative emotions and to find some respite, self-soothe and escape, behaviors in hedonic shopping increased (Gupta & Mukherjee, 2022).

Hedonic motivation in online search and consumer behavior is referred to as the pursuit of sensory, affective, and experiential gratification during the search process (Hirschman & Holbrook, 1982a). Unlike utilitarian motivation, which is goal-driven and emphasizes efficiency (Babin et al., 1994), hedonic motivation is characterized by engagement in exploratory, curiosity-driven, and creates aesthetically appealing interactions. Users with hedonic intent often prioritize enjoyment, novelty, and visual richness over task efficiency, leading to behaviors such as prolonged browsing, engagement with interactive content, and preference for visually immersive search experiences (Chung & Tan, 2004; Novak et al., 2000). This distinction is particularly relevant in digital environments, where visual search tools and recommendation algorithms enhance hedonic experiences by facilitating surprise discoveries (Daugherty et al., 2008).

Online shopping was already well-established pre-pandemic, it took off with the advent of Web 2.0. In the beginning, searching online was quite limited and was nothing like the online shopping experience we have today. At present, it has become a major time-saver with seamless buying and home delivery. E-commerce merchants have innovated to find ways to get their products into their customers's hands faster. The anticipation of receiving packages is also part of the hedonic motivations in shopping (Schnurr & Wetzels, 2020).

“Shopping online” is searching online, as in just looking around, as done while window shopping. An activity to get an idea of what's what, and then usually at a later moment, to make a purchase. Thus, shopping, whether online or in person, is sometimes practiced both in hedonic and utilitarian modes (Setiawan et al., 2020).

Hedonically motivated shopping fulfills a person's desires at times, this could be psychological or emotional needs, for satisfaction or prestige, and at other times to gratify subjective feelings (Widagdo & Roz, 2021). Hedonic shopping fulfills the nonfunctional aspects of consumerism (Lee & Kim, 2018), similar to the window shopping phase: to bring about ideas and procure inspiration through exploration. When a hedonic motivation drives the online shopping experience, there is a readiness to learn, and a need for the visual senses to be stimulated and entertained. This self-pleasing conduct is done in search of awakening, happiness, and fantasy to benefit the mind and body by releasing some tension (Zhao et al., 2016). The time spent is excused as a form of investment in oneself, some "me time" that's quick and accessible. The “idea of something, that can improve our lives”, creates anticipation. The potential for discovery positively influences the state of mind and drives excitement during an online shopping session (Nieuwenhuysen, 2018). The multisensory response that is created by the interaction with the product is stimulating, it causes repetitive behavior from online shoppers who are seeking hedonic experiences. (Hirschman & Holbrook, 1982b).

Utilitarian motivation in online search and consumer behavior refers to a goal-oriented, task-driven approach focused on efficiency, functionality, and problem-solving (Babin et al., 1994). Unlike hedonic motivation, which emphasizes experiential gratification, utilitarian search behavior is characteristically rational, and efficient, where users seek to minimize effort and time while maximizing accuracy and relevance (Davis, 1989) In digital environments, utilitarian users prioritize structured navigation, precise keyword searches, and streamlined interfaces to achieve specific objectives, such as fact-finding information, comparing product specifications, or completing a transaction with minimal distractions (Novak et al., 2000). This distinction is particularly relevant in the design of search engines and e-commerce platforms, where utilitarian features such as filters, autocomplete, and recommendation systems enhance efficiency (Hung et al., 2021).

Research Gap

Despite the growing prevalence of online search technologies, research comparing visual search and textual search in the context of user motivation (hedonic vs. utilitarian) remains limited. Existing studies on online search behavior primarily focus on search efficiency, accuracy, and user satisfaction but often overlook the role of motivation in search preferences. Previous studies have examined visual vs. textual search, but few have explored how motivational factors (hedonic vs. utilitarian) influence user preference and effectiveness. The assumption that visual search naturally aligns with hedonic exploration has not been empirically tested in controlled experimental settings.

Current search interfaces prioritize efficiency but may not fully account for cognitive processes and user expectations based on search motivation. There is limited research on how users navigate and adapt their strategies when searching visually vs. textually.

Understanding the cognitive experiences associated with textual versus visual search would provide valuable insights into user behavior. Additionally, examining whether hedonic and utilitarian motivations interact with the type of search could further clarify their influence on search experiences. This study formulates six hypotheses to compare the cognitive effects—specifically valence, arousal, and dominance—when engaging in online shopping using either visual or textual search under hedonic or utilitarian motivation. The different possibilities are reflected in the Research Model (Figure 1).

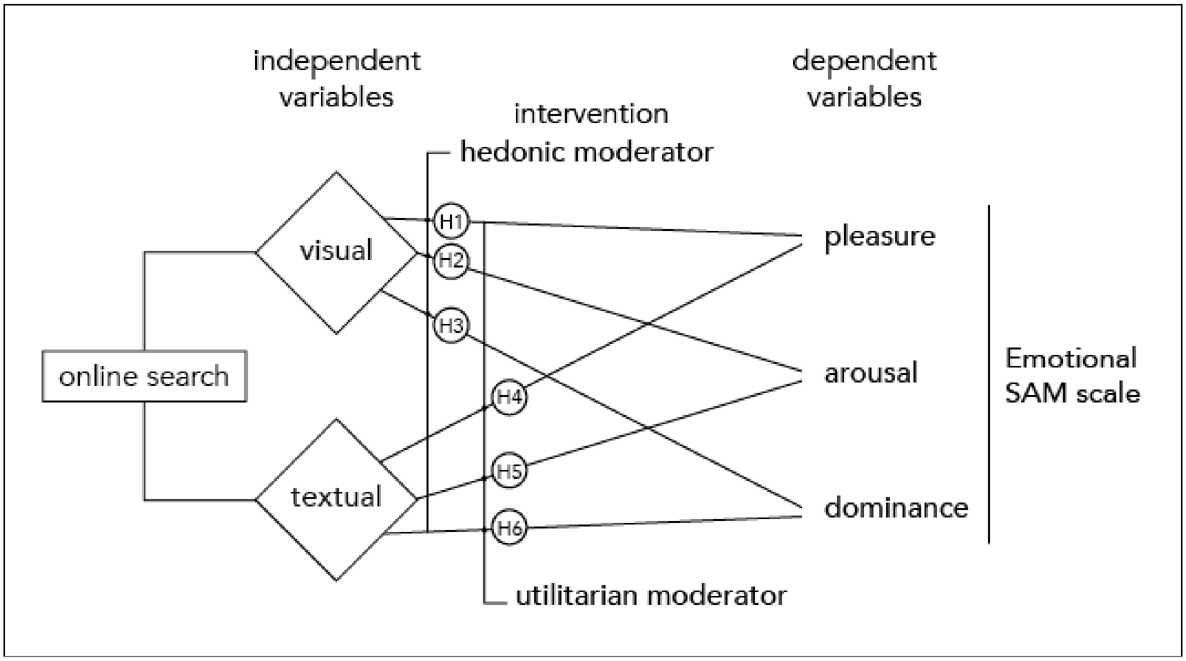

Figure 1 - Proposed Research Model

Hypothesis

H1: During a visual search, a hedonic motivation would yield higher valence.

H2: During a visual search, a hedonic motivation would yield higher arousal.

H3: During a visual search, a hedonic motivation would yield higher dominance.

H4: During a textual search, a utilitarian motivation would yield lower valence.

H5: During a textual search, a utilitarian motivation would yield lower arousal.

H6: During a textual search, a utilitarian motivation would yield lower dominance.

To verify our hypothesis, we used the SAM (Self-Assessment Manikin) scale to measure valence, arousal, and dominance.

Valence

Valence is the valuation of an emotional experience that leads to an emotional response based on the positivity or the negativity of the experience (Barrett, 2006). A positive valence relates to that which is good, valuable, desirable, or attractive, the emotional response to that being emotional appeal. A negative valence relates to badness or averseness, rendering it undesirable or unappealing.

Arousal

Emotional arousal is a physiological activation, associated with sensory stimulation, a state of being awake, or alert. Excitement or energy expenditure is linked to an emotion that is closely related to a person's appraisal of the significance of an event or the physical intensity of a stimulus. Arousal when paired with valence can positively facilitate or negatively debilitate performance.

Dominance

Dominance is the degree to which an individual believes they have control over themselves, around other people or activities, over their feelings, and in their surroundings. It is a personal and situational form of being in control. The lack thereof would look like a feeling of lostness. Dominance assesses a person's feelings of control and influence over their life circumstances versus feelings of being controlled and influenced by others or events.

Chapter 3 Methodology

Introduction

This experimental study was conducted at HEC Montréal to test our participants' online search experiences with textual and visual search in interaction with hedonic or utilitarian motivation.

In the following sections are the details of the experiment, its design, and how it was administered to the participants.

Sampling Strategy

The sampling strategy was non-probabilistic. Recruitment was done in collaboration with Tech3Lab at HEC Montréal, which provided access to Panelfox, a platform to facilitate recruitment, screening, booking, and payment for participants. Participants were paid $20.00 for the experiment which lasted on average 60 minutes, including a post-experiment interview.

The experiment had a total of 33 participants, 22 females and 11 males. Their ages varied between 18 and 58 years old, and they had different living statuses with 19 renters, 6 owners, 7 living with parents, and one who chose not to disclose.

Research Approach

The collection of both quantitative and qualitative data was to have a comprehensive overview of the results. The quantitative data was logged in by the participants by answering post-tasks questions self-assessing their levels of valence, arousal, and dominance on a 5-point SAM scale (Self-Assessment Manikin). For valence, the SAM scale ranges from a smiling, happy figure to a frowning, unhappy figure. For arousal, the SAM scale ranges from sleepy with eyes closed to excited with eyes open. The dominance scale shows the SAM scale ranging from a very small figure representing a feeling of being controlled or submissive to a very large figure representing being in control (Morris, n.d.) (Figure 2). The use of pictograms allows this scale to be universal. In addition, the five-point scale allowed the participants to assess their state of mind and body and capture their first impressions quickly, to move on to execute the next task (Kouroupetroglou et al., 2013).

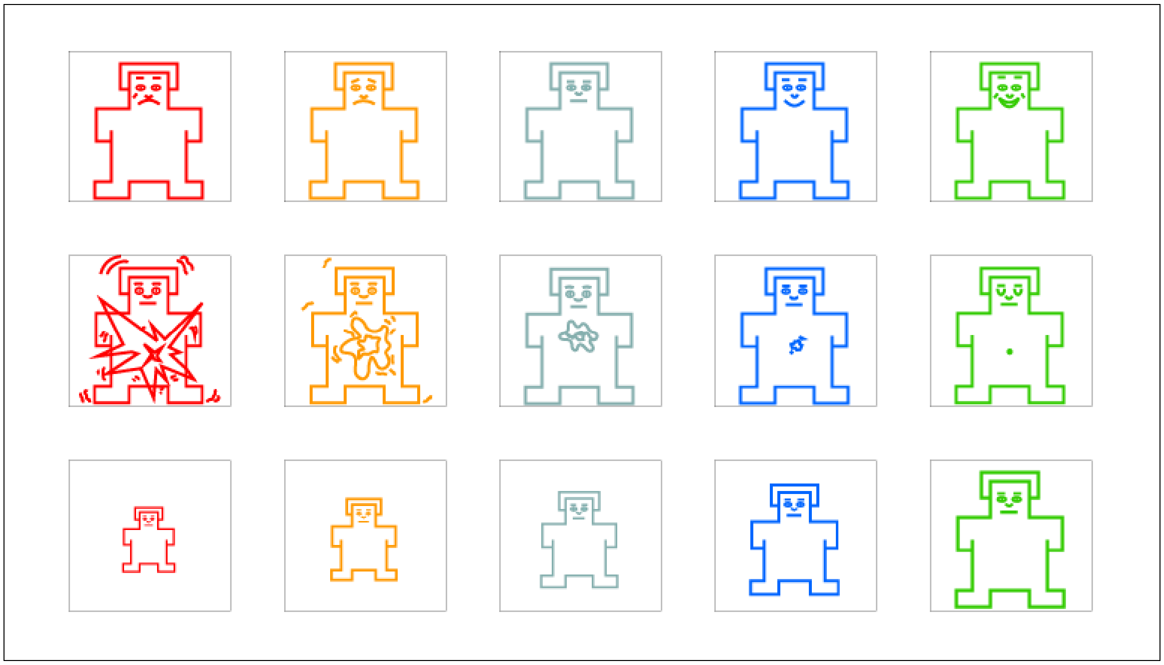

Figure 1 - SAM scales for Valence, Arousal, and Dominance

The qualitative data was collected during a post-experiment one-on-one semi-structured interview of eight questions to complete the quantitive data collected during the experiment. Each participant's answers were transcribed and referred to during analysis; the purpose of the interview was to gain insights into their scores and also aid in the interpretation of the results.

Experimental Design

The study was designed as a 2 x 2 within-subjects experimental design. The independent variables consisted of the 2 types of searches (textual or visual) in interaction with the 2 types of motivations (utilitarian or hedonic) (Table 2). To ensure an even combination between the 2 x 2 independent variables, a randomized task flow on the Qualtrics survey platform was programmed, ensuring that the main independent variables, namely: the search method (textual and visual) were assigned to each participant.

Search type	Moderator type	
	Utilitarian motivation	**hedonic motivation**
Textual search	4 search tasks	4 search tasks
Visual search	4 search tasks	4 search tasks

Table 2 - 2 x 2 experimental design

Set-up and experiment

Each participant performed both visual and textual searches in 2 separate randomized sets of 4 search tasks. Measurements were obtained for the same variables across different conditions, characterizing the study as a repeated measures design.

The data collection was conducted over seven weeks in a room on HEC Montréal's campus. The room was staged with samples of objects found in a typical kitchen: a sink, a faucet, samples of countertops, and backsplash tiles. It also displayed tools for plumbing: a pair of plyers, a plumber's putty, a pipe, and a pipe saw. In addition, interior design magazines with beautiful kitchen designs on the covers were added to offer inspiration (Figure 3).

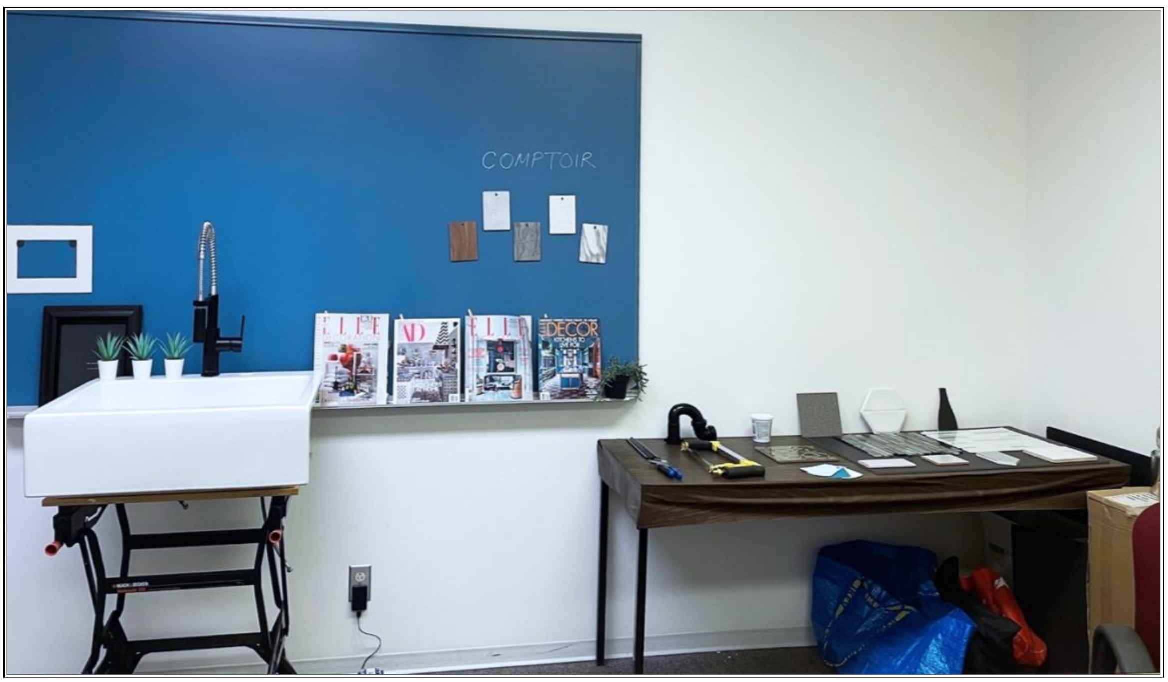

Figure 2 - Room setup

The participants were tasked with searching for objects to renovate a kitchen, ranging from cosmetic to functional changes. A scenario was presented to them, in which a friend who admired our participant's taste in home décor, was soliciting their help to find items for their kitchen renovation. The participants viewed a still image and listened to an audio recording of the fictitious scenario. The setting was controlled by keeping it the same for each participant and limiting any other factors to influence the interactions between the search method and the search motivation.

Scenario

> "Impressed by your recently renovated kitchen your friend has requested your help to find 8 items to get the project started. Among the items, 4 are hedonic items and 4 are utilitarian. The hedonic objects are a farmhouse-style white sink, a farmhouse-styled faucet, samples of backsplash tiles, and some kitchen counter samples. The utilitarian objects, and tools necessary to work on the renovations, consist of a drainpipe, a pipe saw, a jar of plumber's putty, and a wrench to fix the pipes. One of the conditions is that the items need to be sourced locally, so your friend could go and buy them, and encourage local businesses."

At the beginning of every set of 4 search tasks, the context of what a utilitarian or a hedonically motivated search entailed, was reminded in the instruction. As to have them adopt a hedonic or a utilitarian mindset during their searches. The search for objects that appealed to the aesthetic look of a kitchen would put them in an exploratory state of mind while performing the hedonic search. The search for construction tools and objects that had a functional purpose would have them in the utilitarian mode. The participants were encouraged to perform their searches on Google, however, using another browser was allowed. In a randomized way, tasks were then administered starting with a textual or a visual search, in combination with a hedonic or utilitarian moderator (Figure 4).

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
TH	TU	TU	TU	TU	TH	TU	TH	TU	TH	TU	TH	VU	TU	VH	VH	VU	TU	VU	TH	VU	VH	VH	TU	VU	TH	TU	VU	TU	TU	TH	TU	VU
VH	VU	VH	VH	VH	VH	VU	VH	VU	VH	VU	VH	TU	VU	TH	TH	TH	VU	TU	VH	TH	TU	TH	VU	TH	VH	VU	TH	VH	VH	VU	VH	TH

TH: TEXTUAL HEDONIC **TU:** TEXTUAL UTILITARIAN **VH:** VISUAL HEDONIC **VU:** VISUAL UTILITARIAN

Figure 3 - Randomization sequence

To mimic a difficult word search situation, when one lacked the correct words, the description of the search items was purposely kept vague. To perform the visual search, an Apple iPhone was provided to the participants with which they took pictures of the items, to be uploaded onto Google Lens via a USB cable. After each search task was completed, participants were asked to complete a self-assessment (SAM scale), to self-evaluate their level of valence on a 5-point scale from unpleasant (1) to pleasant (5), their level of arousal on a 5-point scale from agitated (1) to calm (5) and their level of dominance from feeling controlled by the interface (1) to being in control of the interface (5). After completing both sets of 4 visual and 4 textual searches, participants were asked about their overall impression of their search experience. Specifically, they were questioned on which search method they enjoyed more, their familiarity with each search method whether visual search was something they would continue to use, and in which instances (Figure 5).

Variables

- Independent Variable: online visual search or online textual search (with moderator)
- Dependent Variables: valence, arousal, and dominance
- Tools: Post-task measures were registered after each task on the Qualtrics platform.
- Scale: The SAM scale was used with icons of each of the 5 states for each emotion.

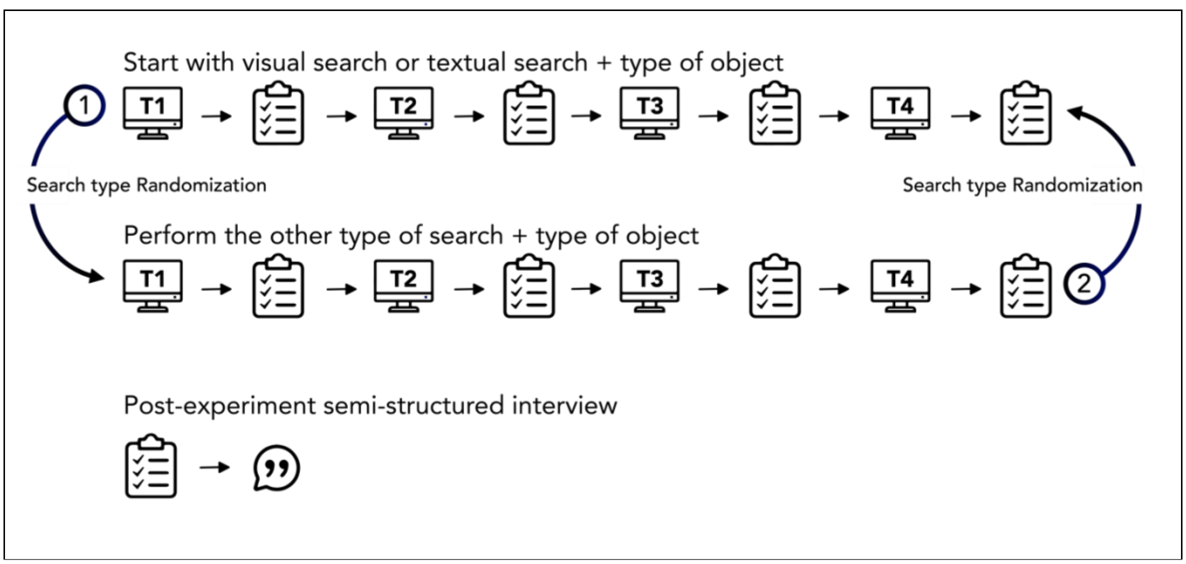

Figure 4 - Experimental procedure

Chapter 4 Results and Analysis

To answer the research question and test the hypotheses, a two-way ANOVA test with repeated measures was used. The goal of the experiment was to compare online visual search to online textual search, by measuring and comparing valence, arousal, and dominance under a hedonic or a utilitarian moderator. Each hypothesis was analyzed according to the dependent variable measured: valence (H1 & H4), arousal (H2 & H5), and dominance (H3 & H6).

The High-Level Summary of Results

The results from our data collection indicated that our dependent variables: valence, arousal, and dominance, all had a strong interaction effect between the search method and the search motivation.

Our sample size being under 50, we had to verify 2 assumptions to determine if the dependent variables varied according to the normal distribution in each of the four groups: «Textual-Utilitarian search», «Textual-Hedonic search », «Visual-Utilitarian search », «Visual-Hedonic search », and if the variance for each dependent variable was equal in each of the same four groups.

To verify the normality assumption, the Shapiro-Wilk test was conducted and indicated that for each variable: valence had 3 out of 4 groups with a normal distribution except for Visual hedonic search, arousal only had one group with a normal distribution; Textual utilitarian search. Dominance had 3 out of 4 groups with a normal distribution except for Textual utilitarian search

The equality of variances was verified using Levene's Test of Equality of Error Variances[a,b]. The analysis indicated equal variance across all four groups, for all the dependent variables, valence, arousal, and dominance.

Once we had established the normality and the variance of the results, we were able to confirm or infirm our 6 hypotheses, and all 6 hypotheses were rejected.

With these limitations in mind, we conducted a 2 x 2 Anova analysis for valence, arousal, and dominance to verify if the interaction effect for each group was statistically significant. A univariate test compared the means for each search method: visual and textual, between the search motivations: utilitarian and hedonic. Indeed, not only did each dependent variable, get a statistically significant interaction between the search method and the search motivation. A clear pattern emerged, demonstrating how the search motivation; hedonic and utilitarian affected the search methods; visual or textual. The tangents were in fact, inversed from what we had hypothesized.

The results indicated that for valence, only visual search had a statistically significant difference of 3.18 in the mean between hedonic and utilitarian search. Arousal did not have a statistically significant difference in the mean scores for any group, arousal is an engagement measure and explains that low arousal is a sign that everything is going well, and therefore efficient. Dominance indicated that visual search had a statistically significant difference of 3.52 in the mean difference between hedonic and utilitarian search.

4.1 Results and Analysis of H1 and H4

Two-way (2x2) model:

Valence *= Intercept + Search Type + Search Object + Search Type x Search Object*

Descriptive Statistics for Valence								
Hypothesis	**Search Method**	**Search Object**	**N**	**Std. Deviation**	**Mean**	**Median**	**Min. on /20**	**Max. on /20**
H1	Visual	Hedonic	17	2.342	<u>13.88</u>	<u>14.00</u>	9	17
		Utilitarian	16	2.205	17.06	17.00	12	20
H4	Textual	Hedonic	16	2.049	15.75	16.00	11	19
		Utilitarian	17	3.553	<u>14.00</u>	<u>15.00</u>	6	19

Table 3 - Mean, median scores, and standard deviation for valence

Our sample size was 33, close to 30, the minimum required sample size, therefore, a verification of the distribution's normality and equality in variance was done.

Assumption on the normality of Valence

We assume the valence variable varies according to the normal distribution in each of the four groups «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Assumption on the variance of Valence

We assume the variance of valence is equal in the four groups «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Detailed results on checking those assumptions are available in the Appendice see Appendix 1.

The Assumption on Normality of Valence was satisfied for three of the four groups, the exception being the group «Visual Hedonic search ». The assumption on variance of valence was satisfied for all four groups.

With these limitations in mind, the outputs of the 2x2 ANOVA analysis for valence are reported in the following tables. The test of between-subject effects for valence did show a statistically significant interaction effect (p-value< 0.001) at 5% for the Search Type with the Motivation (Table 4).

Tests of Between-Subjects Effects for Valence					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	114.071a	3	38.024	5.538	.002
Intercept	15181.990	1	15181.990	2211.131	<.001
Search Type	5.884	1	5.884	.857	.358
Moderator	8.429	1	8.429	1.228	.272
Search Type x Motivation	100.172	1	100.172	14.589	<.001
Error	425.702	62	6.866		
Total	15661.000	66			
Corrected Total	539.773	65			

Table 4 - Variances verification for valence

Table 5 shows the Univariate tests used to compare the means for the search method, Visual and Textual, and the search motivation, utilitarian and hedonic. It turns out that only the Visual search method yielded a statistically significant difference between the two types of motivations. The visual search showed that the utilitarian motivation scored on average 3.18 higher than the hedonic motivation.

Pairwise Comparisons for Valence

Hypothesis	Search Method	(I) Search Object	(J) Search Object	Mean Difference (I-J)	Std. Error	Sig.b
H1	Visual	Utilitarian	Hedonic	3.180*	.913	<.001
		Hedonic	Utilitarian	-3.180*	.913	<.001
H4	Textual	Utilitarian	Hedonic	-1.750	.913	.060
		Hedonic	Utilitarian	1.750	.913	.060

Univariate Tests for Valence

Hypothesis	Search Method		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
H1	Visual	Contrast	83.358	1	83.358	12.140	<.001	.164
		Error	425.702	62	6.866			
H4	Textual	Contrast	25.242	1	25.242	3.676	.060	.056
		Error	425.702	62	6.866			

Each F tests the simple effects of Search Object within each level combination of the other effects shown.
These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Table 5 - Simple effects for valence by search method

In contrast, textual searches, had lower scores on average for utilitarian motivations, by 1.75, compared to the average score for hedonic motivations, however not statistically significant, whether a Bonferroni correction was applied or not (tests at the 0.025 (correction) or 0.05 alpha level) (Table 5).

H1 which stated that during a visual search, a hedonic motivation would yield higher valence, was not confirmed. A visual search with a hedonic motivation did not yield higher scores for valence, the mean was 13.88, which was lower than the mean for utilitarian motivation (17.06), and the difference of 3.18 was statistically significant.

The analysis of **H4, which stated that during a textual search, a utilitarian motivation would yield lower valence, was inconclusive.** Indeed, a textual search with a utilitarian motivation did yield lower scores for valence, the mean for textual utilitarian search being 14, which was lower than the mean of 15.75 for the textual hedonic search. However, the difference was not statistically significant (Table 5).

4.2 Results and Analysis of H2 and H5

Two-way (2x2) model:

Arousal *= Intercept + Search Type + Search Object + Search Type x Search Object*

Descriptive Statistics for Arousal								
Hypothesis	**Search Method**	**Search Object**	**N**	**Std. Deviation**	**Mean**	**Median**	**Min. on /20**	**Max. on /20**
H2	Visual	Hedonic	17	2.551	14.41	14.00	11	18
		Utilitarian	16	3.381	16.69	17.50	10	20
H5	Textual	Hedonic	16	2.604	16.13	17.00	10	20
		Utilitarian	17	3.771	14.71	14.00	6	20

Table 6 - Mean, median scores, and standard deviation for arousal

Assumption on the normality of Arousal

We assume the arousal variable varies according to the normal distribution in each of the four groups «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Assumption on the variance of Arousal

We assume the variance of arousal is equal in the four groups «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Detailed results on checking those assumptions are available in the Appendice see Appendix 2.

The assumption on the normality of arousal was satisfied for only one group « Textual Utilitarian search ». The assumption on the variance of arousal was satisfied for all four groups.

With this in mind, the outputs of the 2x2 ANOVA analysis for arousal are reported in the following tables. The test of between-subject effects for valence did show a statistically significant interaction effect (p-value = 0.019) at 5% for the Search Type with Motivation (Table 7).

Tests of Between-Subjects Effects for Arousal					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	59.529a	3	19.843	2.034	.118
Intercept	15806.263	1	15806.263	1620.258	<.001
Search Type	.297	1	.297	.030	.862
Moderator	3.024	1	3.024	.310	.580
Search Type x Motivation	56.263	1	56.263	5.767	.019
Error	604.835	62	9.755		
Total	16428.000	66			
Corrected Total	664.364	65			

Table 7 - Variances verification for arousal

Table 8 shows the Univariate tests used to compare the means for the search method, Visual and Textual, and the search motivation, utilitarian and hedonic. The Bonferroni correction was set at an alpha level of 2.5%, therefore our p-value = 0.041 was not statistically significant in the difference between the mean scores. The visual search method difference of 2.28 between the higher mean score for utilitarian motivation compared to that of hedonic motivations was not statistically relevant.

Pairwise Comparisons for Arousal						
Hypothesis	**Search Method**	**(I) Search Object**	**(J) Search Object**	**Mean Difference (I-J)**	**Std. Error**	**Sig.b**
H2	**Visual**	**Utilitarian**	**Hedonic**	2.276*	1.088	.041
		Hedonic	**Utilitarian**	-2.276*	1.088	.041
H5	**Textual**	**Utilitarian**	**Hedonic**	-1.419	1.088	.197
		Hedonic	**Utilitarian**	1.419	1.088	.197
Based on estimated marginal means						
*. The mean difference is significant at the .05 level.						
b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).						

Univariate Tests for Arousal								
Hypothesis	Search Method		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
H2	Visual	Contrast	42.687	1	42.687	4.376	.041	.066
		Error	604.835	62	9.755			
H5	Textual	Contrast	16.599	1	16.599	1.702	.197	.027
		Error	604.835	62	9.755			
Each F tests the simple effects of Search Object within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.								

Table 8 - Simple effects for arousal by search method

Likewise, textual searches, had lower scores on average for utilitarian motivations, by 1.42, compared to the average score for hedonic motivations, not statistically significant, whether a Bonferroni correction was applied or not (tests at the 0.025 (correction) or 0.05 alpha level) (Table 8).

H2 which stated that during a visual search, a hedonic motivation would yield higher arousal, was not confirmed. A visual search with a hedonic motivation did not yield higher scores for arousal, the mean was 14.41, which was lower than the mean for utilitarian search (16.69), and the difference of 2.28 was statistically significant.

The analysis of **H5, which stated that during a textual search, a utilitarian motivation would yield lower arousal, was inconclusive**. Indeed, a textual search with a utilitarian motivation did yield lower scores for arousal, the mean for textual utilitarian search being 14.71, which was lower than the mean of 16.13 for the textual hedonic search. However, the difference was not statistically significant (Table 8).

4.3 Results and Analysis of H3 and H6

Two-way (2x2) model:

Dominance *= Intercept + Search Type + Search Object + Search Type x Search Object*

Descriptive Statistics for Dominance								
Hypothesis	**Search Method**	**Search Object**	**N**	**Std. Deviation**	**Mean**	**Median**	**Min. on /20**	**Max. on /20**
H3	Visual	Hedonic	17	4.030	13.35	13.00	6	20
		Utilitarian	16	2.729	16.88	17.00	11	20
H6	Textual	Hedonic	16	2.387	16.31	16.50	11	20
		Utilitarian	17	4.039	15.76	17.00	5	20

Table 9 - Mean, median scores, and standard deviation for Dominance

Assumption on the normality of Dominance

We assume the dominance variable varies according to the normal distribution in each of the four groups: «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Assumption on the variance of Dominance

We assume the variance of dominance is equal in the four groups: «Textual search and utilitarian motivation», «Textual search and hedonic motivation», «Visual search and utilitarian motivation», and «Visual search and hedonic motivation».

Detailed results on checking those assumptions are available in the Appendice see Appendix 3.

The assumption on the normality of dominance was satisfied for three of the four groups, the exception being the group «Textual search and Utilitarian motivation». The assumption on the variance of dominance was satisfied for all four groups.

With these limitations in mind, the outputs of the 2x2 ANOVA analysis for dominance are reported in the following tables. The test of between-subject effects shows that the interaction effect is significant (p-value = 0.018) at 5%, for the type of search with motivation (Table 10).

Tests of Between-Subjects Effects for Dominance					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	120.235a	3	40.078	3.460	.022
Intercept	15998.263	1	15998.263	1381.218	<.001
Search Type	14.094	1	14.094	1.217	.274
Moderator	36.457	1	36.457	3.148	.081
Search Type x Motivation	68.263	1	68.263	5.893	.018
Error	718.129	62	11.583		
Total	16788.000	66			
Corrected Total	838.364	65			

Table 10 - Variances verification for Dominance

Table 11 shows the Univariate tests used to compare the means for the search method, Visual and Textual, and the search motivation, utilitarian and hedonic. It turns out that only the Visual search method yielded a significant difference between the two types of motivations. The visual search showed that the utilitarian motivations scored on average 3.52 higher than the hedonic motivations.

Pairwise Comparisons for Dominance						
Hypothesis	**Search Method**	**(I) Search Object**	**(J) Search Object**	**Mean Difference (I-J)**	**Std. Error**	**Sig.b**
H3	**Visual**	**Utilitarian**	**Hedonic**	3.522*	1.185	.004
		Hedonic	**Utilitarian**	-3.522*	1.185	.004
H6	**Textual**	**Utilitarian**	**Hedonic**	-.548	1.185	.646
		Hedonic	**Utilitarian**	.548	1.185	.646
Based on estimated marginal means						
*. The mean difference is significant at the .05 level.						
b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).						

Univariate Tests for Dominance								
Hypothesis	**Search Method**		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
H3	**Visual**	**Contrast**	102.246	1	102.246	8.827	.004	.125
		Error	718.129	62	11.583			
H6	**Textual**	**Contrast**	2.473	1	2.473	.214	.646	.003
		Error	718.129	62	11.583			
Each F tests the simple effects of Search Object within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.								

Table 11 - Simple effects for dominance by search method

In contrast, textual searches, had a lower average score for utilitarian motivation, by only 0.55, compared to the average score for hedonic motivations and not statistically significant, whether a Bonferroni correction was applied or not (tests at the 0.025 (correction) or 0.05 alpha level) (Table 11).

H3 which stated that during a visual search, a hedonic motivation would yield higher dominance, was not confirmed. A visual search with a hedonic motivation did not yield higher scores for dominance, the mean was 13.35, which was lower than the mean for utilitarian search (16.88), and the difference of 3.52 was statistically significant.

The analysis of **H6, which stated that during a textual search, a utilitarian motivation would yield lower dominance, was inconclusive.** Indeed, a textual search with a utilitarian motivation did yield lower scores for dominance, the mean for textual utilitarian search being 15.76, which was lower than the mean of 16.31 for the textual hedonic search. However, the difference was not statistically significant (Table 11).

Chapter 5 Discussion

We suspected that visual and textual searches would generate different cognitive experiences when performed under hedonic or utilitarian motivation. In this study, the goal was to compare online visual search to online textual search and verify the impact each search method had on emotional experiences. The plan was to measure three emotions on the SAM scale: valence, arousal, and dominance, and subsequently, compare the scores for the two types of searches: visual or textual, in interaction with the moderating factors: utilitarian or hedonic motivations. In complement to our initial hypothesis, a post-hoc analysis identified unexpected relationships, highlighting potential underlying factors that warranted further investigation.

Second analysis of the valence results

Valence is the emotional value or worth of an experience and leads to a response based on the positivity or the negativity of the experience. A positive valence is good and creates appeal, whereas a negative valence is bad generating avereseness.

The analysis of our data revealed that the user's valence mean scores were significantly higher when performing a textual hedonic search compared to a visual hedonic search. The mean for the visual hedonic search was 13.88, the lowest score. Our H1 hypothesis which stated that during a visual search, a hedonic motivation would yield higher valence, was not confirmed. The results indicated that the interaction goes the opposite way (see Figure 9).

When visual search was combined with a utilitarian search the mean for valence was the highest score at 17.06 (Figure 9). Notably, participants found visual search more enjoyable when they were searching for objects that were functional such as the saw or the plumber's putty.

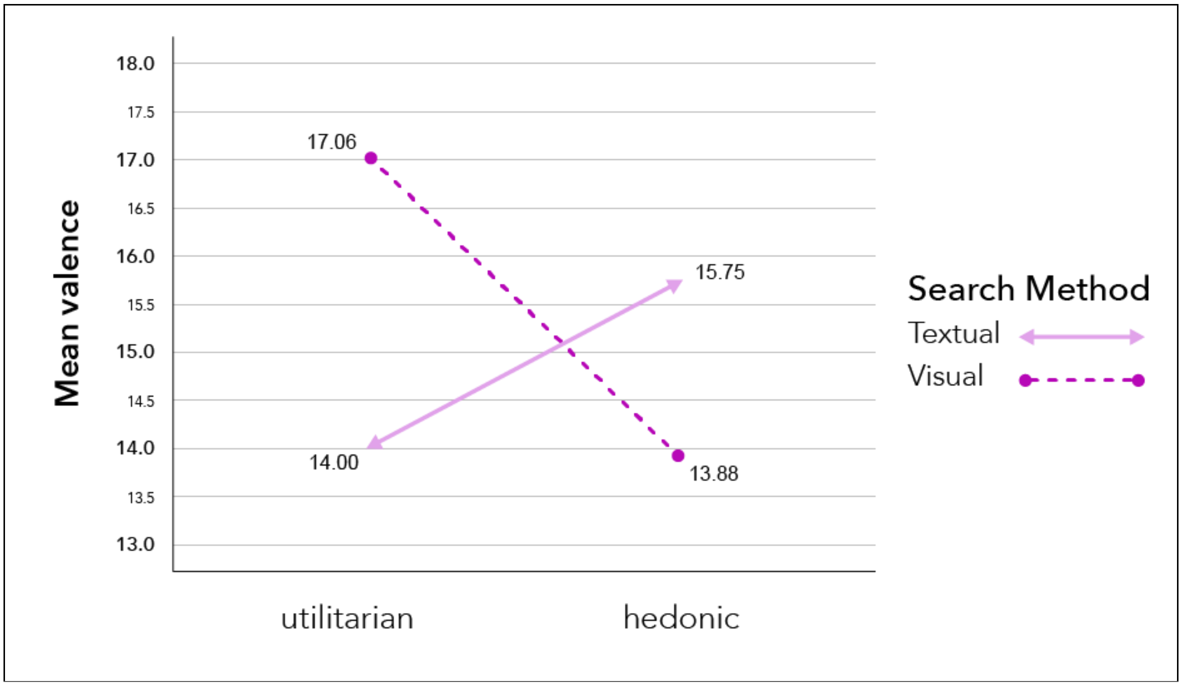

Figure 5 - Distribution curves for valence variable for all groups

This indicates that visual hedonic searches required greater cognitive effort from the participants. The post-experiment answers provided a clearer understanding of their searching and finding process. The participants were eager and deliberate in letting us know when the searches were difficult, and how this impacted their perception of finding what they were searching for.

For our experiment, cognitive effort consisted of behaviors that involved clicking on irrelevant search results, getting poorly ranked results, and instances when extra time was necessary to understand the results. Simply put, the challenge of finding exactly what they were looking for contributed to increasing our participant's cognitive load.

Some hedonic searches demanded greater efforts to search and find, such as the countertop and the backsplash tiles. Using visual search was too much work, it was unappealing in terms of finding exactly what they were searching for. P12 said:

> Visual search, was complicated, more demanding, and not practical, so much so that they would have preferred to physically go to the store or perform a textual search. Taking a picture of the object added to the aggravation and laboriousness. The small amount of options made them feel stuck with such results. (Translated from French, see Appendix 4 for original French).

Similarly, P16 said:

> Visual search was fun but more demanding because it required some adaptation for the search which added complexity to the task, in addition, the results of the product often came from international big box stores and not Québec's merchants. (Translated from French, see Appendix 4 for original French).

Now when it came to the textual utilitarian search for emotional valence, the mean score was 14.00, and the mean score for visual hedonic was 13.88. The textual utilitarian score was not lower than the visual hedonic score. Our H4 hypothesis which stated that during a textual search, a utilitarian motivation would yield lower valence, was not confirmed. The participants found the textual utilitarian search slightly more pleasant, than visual hedonic search when measuring for valence. P15 said:

> The textual search results were precise, targeted, and coherent, these factors made them feel confident in the search results. (Translated from French, see Appendix 4 for original French).

The interaction effect was significant at an alpha of less than 0.001, between the search method and search motivation when we measured for valence (Figure 9).

Participants found the visual utilitarian search was good because it was precise and coherent, making it desirable. Searching for the saw or the pipe was appealing using visual search.

Second analysis of the arousal results

Emotional arousal happens when an individual is physiologically activated, depending on the appraisal of the stimulus. Arousal can either facilitate or debilitate performance. Arousal needs to be paired with valence to gain a positive or negative value. For example, high arousal with low valence can result in frustration whereas low arousal and high valence can mean a zen-like feeling about the search experience.

For emotional arousal, the mean score for the visual hedonic search was 14.41, in this instance also the lowest. Our H2 hypothesis which stated that during a visual search, a hedonic motivation would yield higher arousal, was not confirmed.

For the textual utilitarian search, the mean score for arousal was 14.71, and the mean score for visual hedonic was 14.41. The textual utilitarian score was not lower than the visual hedonic score. Our H5 hypothesis which stated that during a textual search, a utilitarian motivation would yield lower arousal, was not confirmed. For both of our hypotheses' on arousal, the difference between the mean scores was not significant.

There was a significant interaction effect, between the search method and the search motivation for arousal (Figure 10), at an alpha of 0.019.

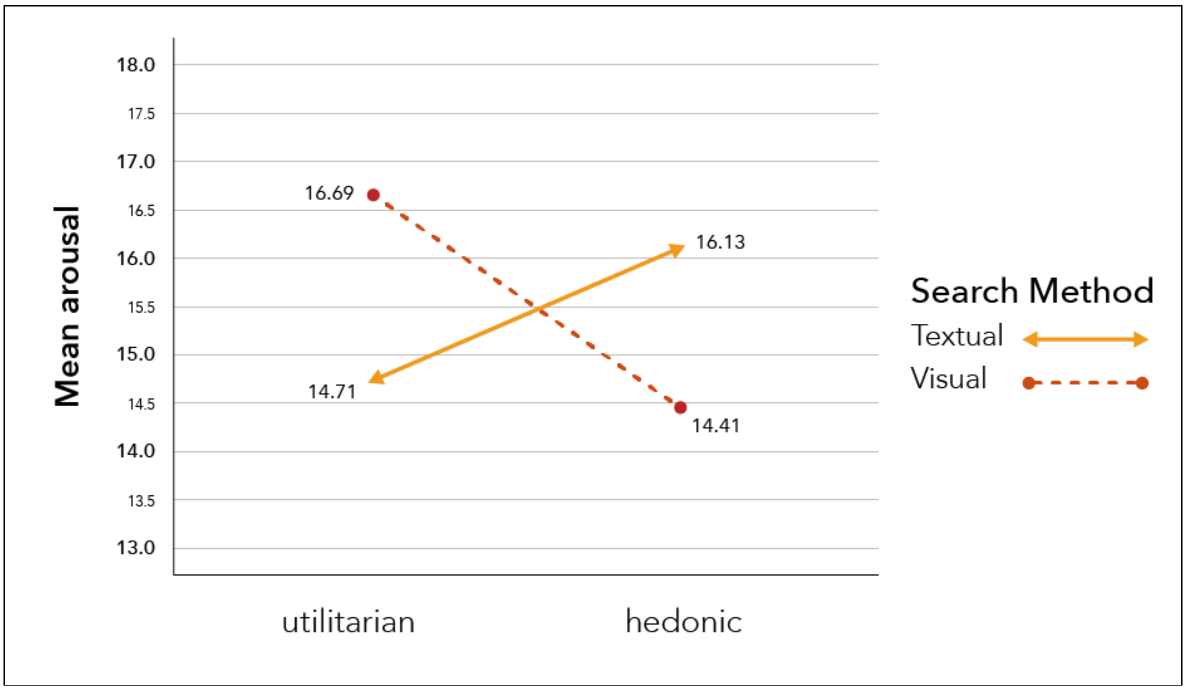

Figure 6 - Distribution curves for arousal variable for all groups

Visual search was more stimulating when performing a utilitarian search. While performing a hedonic search, the method that tallied higher arousal scores, was while searching textually. P13 said:

> Visual search was less stimulating yet efficient, it was limiting if you wanted to be inspired. The search depended on the end goal and found visual search practical. (Translated from French, see Appendix 4 for original French).

Second analysis of the dominance results

The measure of dominance is the degree to which an individual believes they have control over themselves and around other people or activities. The opposite is the lack of control.

Finally, the visual hedonic search gave a mean score of 13.35, the lowest score for dominance. Our H3 hypothesis which stated that during a visual search, a hedonic motivation would yield higher dominance, was not confirmed. The results indicate an inversion. Frequently, participants felt the most dominance when they were conducting a visual utilitarian search.

The functional items, the pipe or the wrench, did not require too much effort to find. The textual hedonic search, made the participant feel more in charge of the search.

For the textual utilitarian search, the mean score for dominance was 15.76 and the mean score for visual hedonic was 13.35. The textual utilitarian score was not lower than the visual hedonic score. Our H6 hypothesis which stated that during a textual search, a utilitarian motivation would yield lower dominance, was not confirmed. The participants felt more dominant when they searched hedonically using textual search. P30 found the textual search:

> Offered a greater opportunity to guide the search, to be more precise and directive. Whereas the visual search had no freedom to choose, the results were imposed. (Translated from French, see Appendix 4 for original French).

Here again, the results showed a significant interaction effect, between the search method and search motivation for dominance with an alpha of 0.018 (Figure 11).

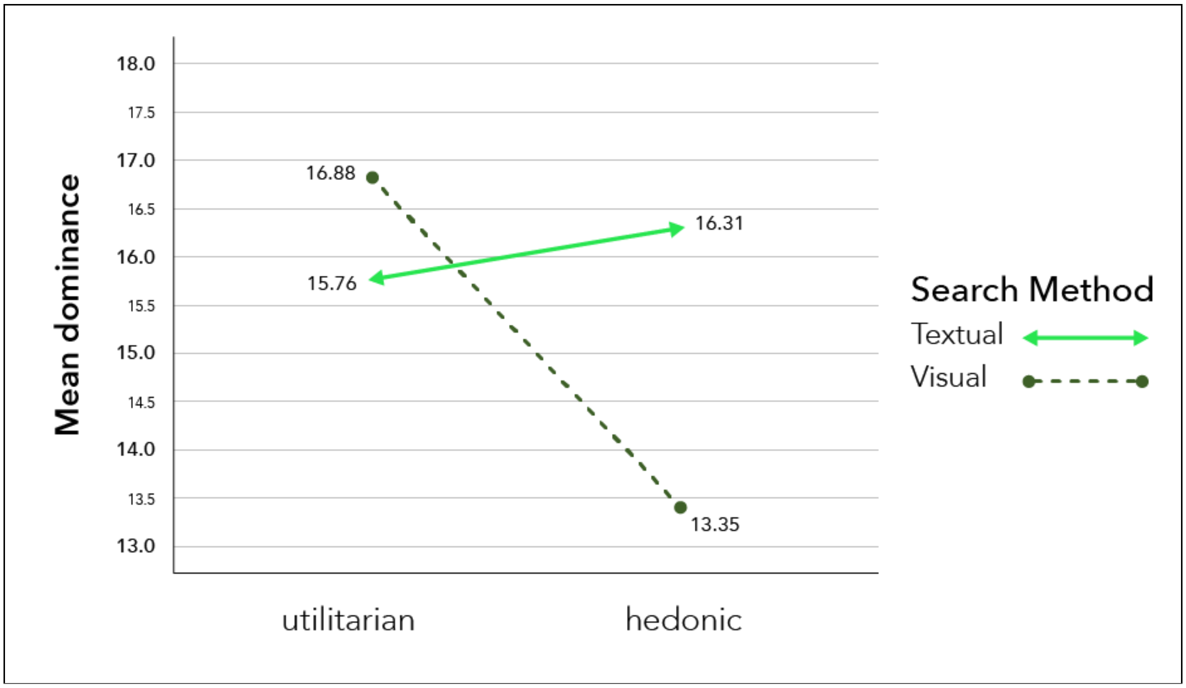

Figure 7 - Distribution curves for dominance variable for all groups

The ability to guide the search allowed our participants to feel more dominant when searching for the wrench during visual utilitarian searches.

The pattern we expected did not match the cross pattern we got from our data results. This pattern was an inversion from the pattern we hypothesized and this was quite an insight. The search method was highly influenced by the search motivation, and vice versa. Hence, a significant interaction effect between the search methods and search motivations.

Visual Searches

We predicted that visual search would score higher for all three dependent variables, valence, arousal, and dominance when the motivation was hedonic. What we got instead, was the highest scores for the visual utilitarian motivation searches. The hedonic visual search scores had the lowest scores for all three emotions (see Figure 12).

Textual Searches

We predicted that the textual search would score the lowest, for the same three dependant variables when the motivation was utilitarian. In this instance also, the textual hedonic motivation search means scored the second highest in the overall mean scores. A close third was for textual utilitarian motivation searches, not the lowest.

The participant's answers gave clarity to their frustrations during visual searches. The top three comments regarding the visual hedonic search for the sink, faucet, backsplash, and countertop, were lack of choice, frustration, and failure to geolocate. Many factors contributed to the helplessness felt during the visual hedonic search, in particular, lack of variety or irrelevant image results. These contributed to leaving the participant with a feeling of an unaccomplished search, or a sense of failure in an exploratory visual hedonic search. As for textual searches, the main issue was the difficulty in wording the search, when the participant wasn't familiar with the object they were searching for.

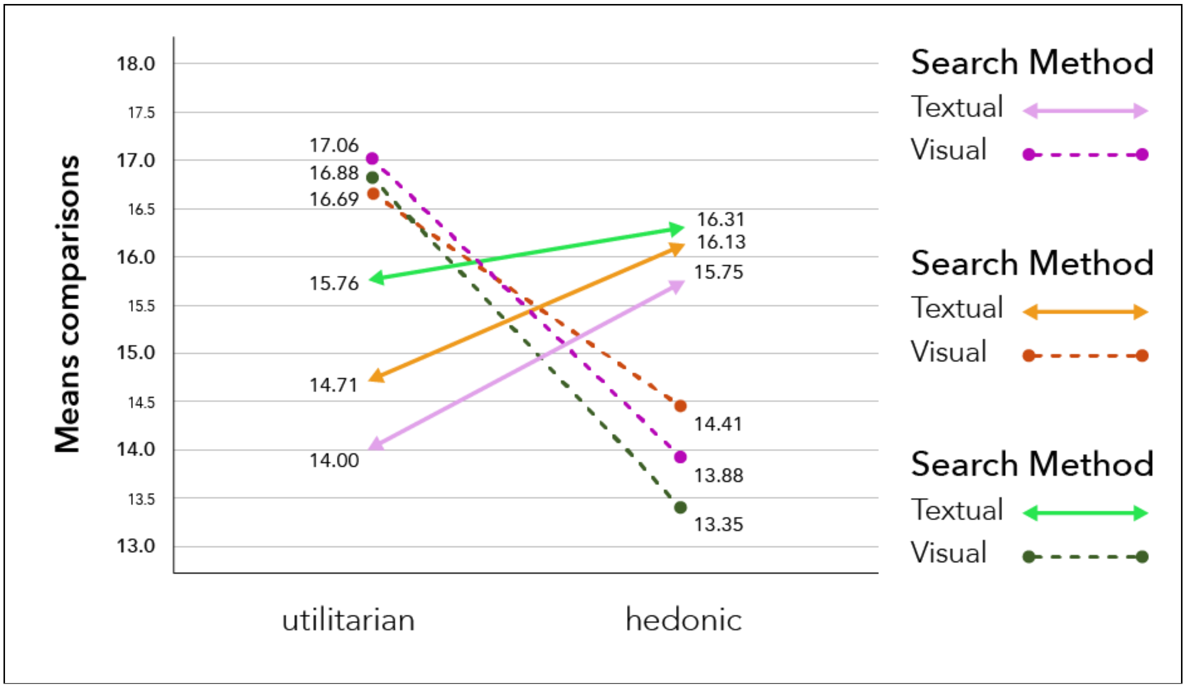

Figure 8 - Distribution curves for all variables for all groups

The use of visual references we thought, would remove some of the search frictions. They did this when the search was utilitarian. However, for the hedonic searches, instances when one must describe something and doesn't have the right words, led us to assume that visual search results would offer more variety and would be similar to searching in everyday life. The exposure to things would be much greater and would mean less time spent searching.

Unfortunately, visual search demanded higher cognitive effort when searching hedonically according to the data we collected.

Cognitive effort

The experiment relied on participants using Google Lens to do their visual search, however, the available technology felt inadequate for the participants' needs. They were disappointed by the cognitive efforts invested to execute visual searches. This had an impact on their hedonic search experience with image search. For some, it diminished their expectations of getting satisfying search results as their visual hedonic search progressed. P06, expressed:

> Visual search was frustrating, from the start on Google Canada results for the countertop and backsplash resulted in grills, it was less efficient. (Translated from French, see Appendix 4 for original French).

P 18 also expressed:

> It recognized the object immediately, however within the proposed results, you have to look carefully and pay close attention because even when it is similar, the details don't match up. A professional would be able to tell the difference. (Translated from French, see Appendix 4 for original French).

Visual similarity bias

One of the participants, P24, summed up well both types of searches:

> Visual was best suited to find the exact product, it output the exact match as the input image. Whereas textual search offered a variety of products and more choices. You just needed to specify what you wanted. (Translated from French, see Appendix 4 for original French).

This explains the higher average scores for valence and dominance while performing a visual utilitarian search. The utilitarian search goal was to find the best match quickly and efficiency was key. The objects that were searched for were technical and precise, and the state of mind was focused on finding the best option in the least amount of time. In contrast, for visual hedonic searches, the participant's search intent was to have variety. The lack thereof took control away from the searcher. P19 said:

> Visual search was more precise and uniform, denying the searcher from any variations from the item, or any extra features and functionalities. (Translated from French, see Appendix 4 for original French).

As discussed earlier, the testimonials, backed by the quantitative results, indicated that during the visual hedonic search, the option to choose was limited or non-existent. The faucet and the sink were objects that complement each other. When the search results were identical to the original image and variety was expected, there were no other options, no way to browse, and hence no control to make a selection. Arnon Dagan (2023), expanded on the "Visual similarity bias," whereby the participant, after inputting an image query, only received results that were identical, or very similar to the initial query (Dagan et al., 2023). This bias occurs because programmers use an algorithm to extract the best-matched image (Pan et al., 2007). At the core, this algorithm is doing its job too well and as a consequence, the results are very limited in diversity. This unfortunately tripped up the participants who wanted variety in the object they were searching for, from their uploaded search image. If the objects had some similarity with different characteristics, or were different in the look with similar characteristics, it would have provided some opportunity to choose. They wanted options, and to not have any created a bias, that was unique to visual search results and not observed during textual search results.

Visual search results lack diversity, lack of relevance

The algorithms behind image retrieval, ranking, and presentation of results were not programmed for diversity in visual search results. In our initial instructions for a hedonic search, we encouraged participants to make a selection according to their style, on variations from the reference object we had in place for them, to photograph and upload. We intended to offer a starting point on Google Lens. P10's comments explain the low scores:

> There was more control with textual searches, which enabled deeper searches and diverse results. Sure, a visual search was quick when you wanted the exact match. (Translated from French, see Appendix 4 for original French).

Participants were guided toward conducting a hedonic search for four objects: a sink, a faucet, a countertop, and a backsplash. These items were showpieces that brought the kitchen together. To look coherent, these items are all chosen with purpose. However, in our experiment, they would be searched separately. The farmhouse-style sink and faucet were there to give guidance and create a constraint. The results, backed by the testimonials, indicate that during the visual hedonic search, the option to choose was limited or non-existent. The assumption was that similar to in-person shopping, the results page would present the item along with other items in close variations to it. Instead, the results page presented multiples of the same image result as the input image, it offered few alternatives to the original because the browser was coded to find the best match.

Furthermore, all four objects chosen for hedonic search had their challenges during visual searches. Some resulted in the exact match some with completely irrelevant results. For example when P06 was searching for a black hexagonal subway tile for the backsplash, (Figure 13) the search results came up with a metal grill (Figure 14). The lack of relevant results flawed the participant's experience and didn't reflect positively on them. It not only prolonged their search times, it also forced the participants to scroll down on the result page to check for more options. These results made it clear that the visual search was looking for patterns and not for categories of objects. This might explain the low scores dominance scores for visual hedonic searches.

Figure 9 - Black hexagon subway tile

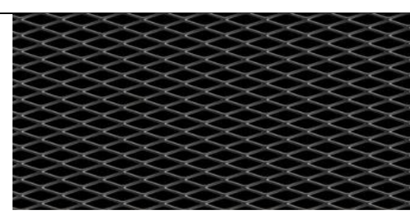

Figure 10 - Image result of grill

Textual search had variety

Textual search results offered a gamut of possibilities because the search was able to cast a wider net. Textual search has been around longer and had time to evolve into a user-friendly tool. The internet is a big melting pot, a bit of a wild west. Searching online has been done with words from the beginning. The organization of items, done with tags and metatags, facilitates associations to similar categories and then provides varied results. A system based on semantics analyzes the tags and metatags that are attached to chunks of information as well as to images. Therefore any search online begins with keywords, and the result reels in whatever is tagged with them.

In-person search

In everyday life, people are accustomed to search with their eyes. Our brain is wired to start a search visually as we've done in person forever. Our eyes guide us and eventually, we read to confirm or infirm what our brain is perceiving. There's a back-and-forth between viewing the visual elements and reading the textual specs. Just as we reach for the cereal box, we view it at first, make associations from its design, glance at the name of the product, and read it in a split second to check that we are not dealing with a copycat.

This sequence is flipped when searching online: we start by typing in specific keywords, and from the multiple results we click to narrow these down further. Once again a back and forth between reading texts and viewing visual elements is also done when online searching. After one or two clicks, we have access to a verbal & visual representation of different options (Figure 12).

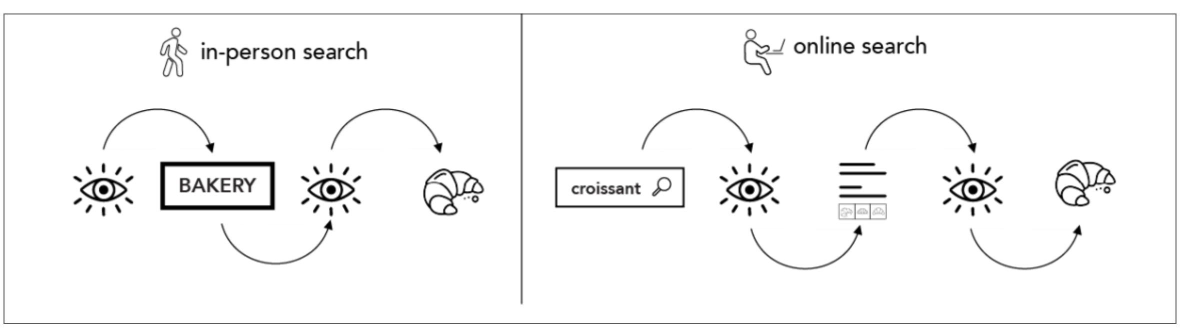

Figure 11 - In-person search versus Online search

The insight that has emerged from our study is that searching online is not aligned with the way we search offline. Since we developed eyeballs, we've been guiding ourselves through them. Reading came along only 5000 years ago, and all humans don't have the privilege of literacy. This begs the question: Wouldn't it be pertinent, to have a human-centered search process? To have the option to choose how we start our online search? And perhaps develop different searching and finding strategies online, that are more aligned with how we search in real-life. Because there are as many ways of searching and finding in real life, yet online, we only have one. We'd like to suggest that yes, we would like more than one search option. Searching online visually or textually involves using different search strategies, and adapting these according to the search topic.

The topic of searching and finding is highly pertinent at this time, because of the growing use of AI in our search process (Statista Market Insights, 2024).

Chat GPT or Google Gemini, are forms of generative AI that are becoming integrated into our daily use because they feel very intuitive or “natural”. The chatbot is trained using Large Language Models (LLM) and has conversational capabilities enhancing the potential to drastically change what users expect from searching (Gurdeniz, Hosanagar, 2023). Generative AI is on the cusp of an unprecedented era, it has the potential of transforming online search. Presently, SearchGPT is still in the prototyping phase, developing searching conversationally. The conversational interface will enable users to refine queries and deepen their understanding through follow-up questions and provide results in audio, video, and image formats, all new ways of searching and finding in real time.

Future research direction

We are the pioneers in experiencing the AI boom that is Generative AI, to interact with machines in a more human-centered way. This begs the question, why not use this opportunity, in this moment in time to shape searching the way we do so spontaneously offline, by performing a search starting with a visual cue? The issues our participants had when searching visually such as ranking and relevance, would taper off with time.

After all, Generative AI looks at diminishing the friction in human-machine interaction by using a combination of natural language processing and machine learning to respond innately, so starting a search visually like we do inherently fits in nicely with the goals of generative AI.

Chapter 6 Conclusion

This study investigated the user experience of searching and finding in an online shopping context. The research goal was to compare online visual search to online textual search and to measure the emotional impacts on valence, arousal, and dominance when searching with a hedonic or utilitarian motivation. We hypothesized that a visual hedonic search would lead to higher scores on valence, arousal, and dominance. Our hypothesis was based on the assumption that in-person shopping when done with a hedonic motivation was more enjoyable. We therefore speculated that the online experience would be similar to the in-person experience. The results were revealed to be different, for our three measures on the SAM scale (valence, arousal, and dominance) textual hedonic search always had the highest mean scores and beat hands down the visual hedonic search. Visual search did record higher mean scores when searching with a utilitarian motivation. The visual hedonic search results were unsatisfactory, they demanded more effort, and there was a lack of variety and relevance in the resulting images. These frustrations meant the participant's expectations when searching online were not met. It also indicated that visual hedonic search needs a different searching strategy that is not based on the algorithms used for textual searches. Presently, visual search is perfect if you want to find an exact match, which is why visual utilitarian search scored higher than visual hedonic search.

Hedonic search in an online setting is meant to be enjoyable, the visual representation aids in the appreciation of the product. The study found that visual hedonic search is not well served online, even if the visual search interface is available, it is not adapted to accommodate our habitual visual searching process. Because the online search process is inverted when compared to the offline search process, i.e., online starts with text then comes the visual, as opposed to starting from a visual cue. We recommend the continued development of more human-centered tools that mirror what is used in regular offline searches, that is with visual cues. We believe Generative AI will in effect, over time, reduce the frictions that occur during visual hedonic searches.

Limitations

As with any other study, our study had limitations. Firstly, the population for our study was recruited mainly from the University's student body. Students were overrepresented, in our sample size, and females composed two-thirds of the sample population. Second, for the context of our study, a greater number of homeowners would have experienced a home renovation and therefore they could have had a greater involvement in the study. To alleviate this limitation, a different and more generic context, less geared towards a segment of the population could be chosen. A third limitation was the budget, which limited the greater number of participants. A bigger sample would have allowed greater insights. Finally, access to equipment to measure physiological measurements to test unconscious responses would have also enabled us to cross-check participants' physiological responses with their self-evaluated answers.

Contributions to the field of user-experience

We derived that visual hedonic search is not the same experience as in real-life visual hedonic search. We have identified the cognitive search patterns associated with on and offline search processes. A human-centered approach to online search would empower users by offering flexibility in how they choose to begin their search. In real life, people will search and discover information in diverse ways—sometimes by asking others, browsing through physical spaces, following visual cues, or even stumbling upon what they need by chance. However, online search has largely been restricted to text-based queries, limiting users to a single mode for exploration. The expansion of search options would create systems that align with the varied ways humans naturally think, search, and find.

Context-aware search could tailor results based on location, previous behavior, or intent, improving seamlessness. In other instances, a voice search would allow a more conversational interaction, closely resembling how we ask for information in real life.

Different search strategies come into play depending on the topic, task, or user preference. A designer searching for inspiration may find image-driven search more valuable, while a researcher might rely on structured keyword queries. By integrating multiple search pathways—text, image, voice, and contextual awareness—we would benefit by creating a more intuitive and effective search experience that adapts to individual needs, making information discovery more accessible, efficient, and natural.

Our findings challenge the common assumption that visual search is naturally suited for hedonic exploration. Contrary to our hypothesis, participants found visual search to be more effective for utilitarian searches, where specificity and goal-oriented behavior were prioritized. In contrast, textual search proved more conducive to exploratory, hedonic searching, as it provided greater flexibility in navigating and discovering options. This study adds to existing literature by refining our understanding of search behaviors and motivations, demonstrating that the fit between search modality and motivation is more nuanced than previously thought.

Practical Contributions

Our findings highlight critical pain points in online search experiences, particularly in visual search usability. As generative AI continues to evolve, this study underscores its potential to transform visual search interfaces, making them more intuitive and aligned with user needs. The insights gained from this research can inform UX designers, search engine developers, and e-commerce platforms in refining their search algorithms and interfaces to better accommodate both hedonic and utilitarian search behaviors.

Individuals rely on both visual and textual channels to cross-verify information, with visual cues typically processed first, followed by textual confirmation. In real-world contexts, this sequential information processing has been fundamental to human cognition for over 5,000 years. However, contemporary digital search tools do not fully align with these natural search behaviors, potentially limiting their effectiveness in supporting intuitive information retrieval. (Figure 13).

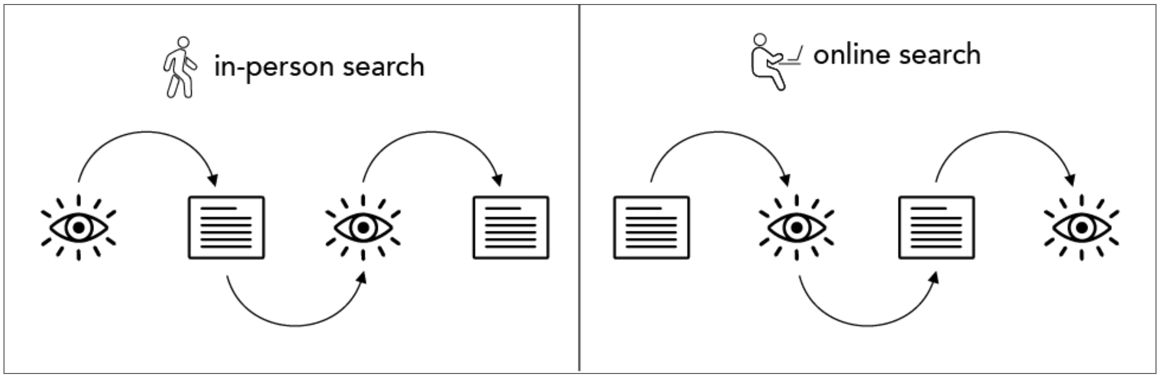

Figure 12 - In-person search versus Online search

In summary, this research offers new insights into online search behaviors, proposes a methodological framework for future investigations, and underscores the necessity of developing more adaptive and human-centered search technologies.

Appendice

Appendix 1

Descriptive Statistics for Valence								
Hypothesis	Search Method	Search Object	N	Std. Deviation	Mean	Median	Min. on /20	Max. on /20
H1	Visual	Hedonic	17	2.342	13.88	14.00	9	17
		Utilitarian	16	2.205	17.06	17.00	12	20
H4	Textual	Hedonic	16	2.049	15.75	16.00	11	19
		Utilitarian	17	3.553	14.00	15.00	6	19

Table 3 - Mean, median scores, and standard deviation for valence as shown on p.36

Visual search got on average higher median scores compared to textual searches, the dispersion of textual search was higher than the dispersion of visual search. Each level has one outlier, at the bottom of the distribution. (Figure 6). Scores for utilitarian motivations were higher, however more dispersed than scores for hedonic motivations

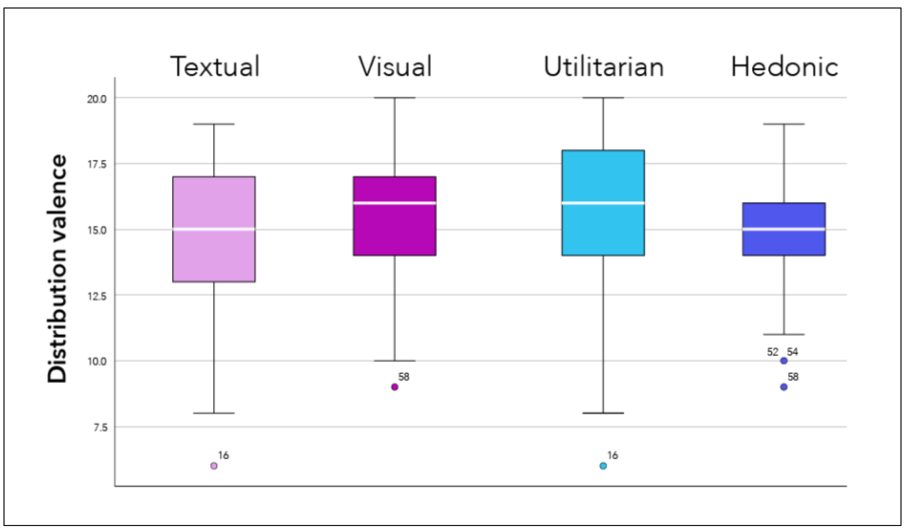

Figure 13 - Distribution curves for valence variable for all groups

Assumption on the normality of Valence

To check the normality assumption, the Shapiro-Wilk test was used, recommended when the sample size is small (less than 50 observations, Royston (1982)). The null hypothesis for a Shapiro-Wilk test states that there is no difference between the results distribution and a normal distribution. The alternative hypothesis is that there is a difference if the p-value is less than 0.05, then the null hypothesis must be rejected as the data is not normal.

In this instance, at a 5% significance level, the normality assumption for the group «Visual search and Hedonic motivation» was not confirmed, and the p-value was 0.049 (Table 12, Figure 14). The three other groups were normally distributed. The assumption on Normality of Valence was satisfied for three of the four groups, the exception being the group «Visual Hedonic search ». The assumption on variance of dominance was satisfied for all four groups.

Test of Normality for Valence

Hypothesis	Search Method	Search Object	Kolmogorov-Smirnova			Shapiro-Wilk		
			Statistic	df	Sig.	Statistic	df	Sig.
H1	Visual	Hedonic	.177	17	.164	.891	17	.049
		Utilitarian	.127	16	.200*	.945	16	.421
H4	Textual	Hedonic	.236	16	.017	.928	16	.228
		Utilitarian	.140	17	.200*	.949	17	.436

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 12 - Normality verification for valence

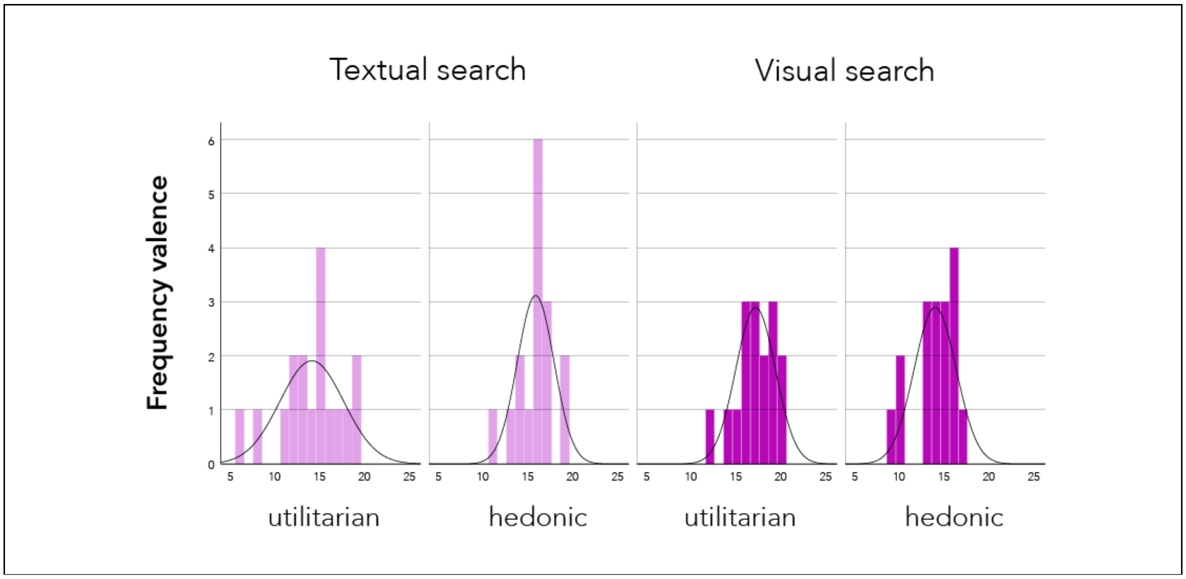

Figure 14 - Frequency curves for valence variable for all groups

Assumption on the variance of Valence

To measure variance we used Levene's Test of Equality of error variances. Levene's test is an inferential statistic used to assess the equality of variances for a variable calculated for two or more groups. If the p-value for the Levene test is greater than 0.05, then the variances are not significantly different from each other (i.e., the homogeneity assumption of the variance is met). If the p-value for Levene's test is less than 0.05, then there is a significant difference between the variances. At a 5% significance level, the assumption of equality of variances across the four groups was defined by the two levels of each factor and was not rejected by the Levene test based on the mean (Table 13).

Levene's Test of Equality of Error Variances[a,b]					
		Levene Statistic	**df1**	**df2**	**Sig.**
Valence	Based on Mean	1.847	3	62	.148
	Based on Median	1.570	3	62	.206
	Based on Median and with adjusted df	1.570	3	46.543	.209
	Based on trimmed mean	1.830	3	62	.151
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.a,b					
a. Dependent variable: valence					
b. Design: Intercept + Search Type + Search Object + Search Type x Search Object					

Table 13 - Variances verification for valence

Appendix 2

Descriptive Statistics for Arousal								
Hypothesis	Search Method	Search Object	N	Std. Deviation	Mean	Median	Min. on /20	Max. on /20
H2	Visual	Hedonic	17	2.551	14.41	14.00	11	18
		Utilitarian	16	3.381	16.69	17.50	10	20
H5	Textual	Hedonic	16	2.604	16.13	17.00	10	20
		Utilitarian	17	3.771	14.71	14.00	6	20

Table 6 - Mean, median scores, and standard deviation for valence as shown on p.39

The boxplot shows, that for hedonic motivation search, the left of the arousal score distribution (below the median) is much more dispersed than the right of the distribution. Values in the third quartile are clustered with the median.

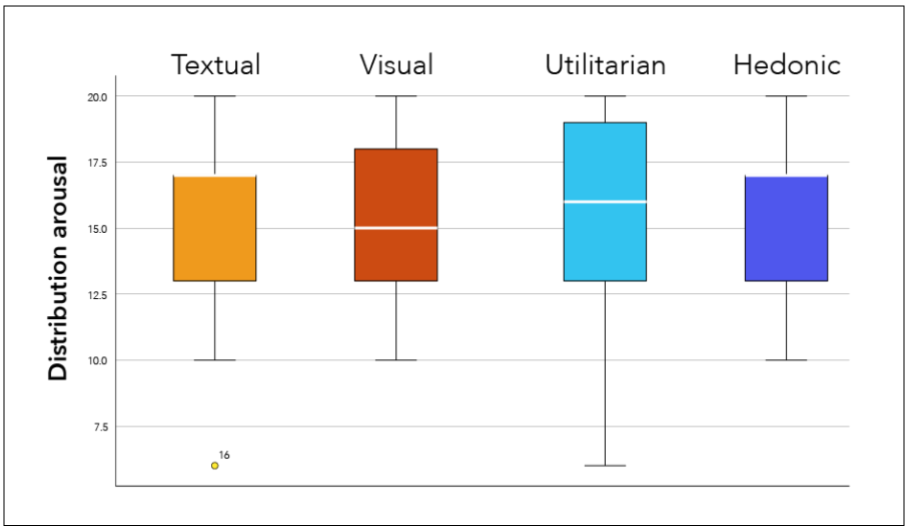

Figure 15 - Distribution curves for arousal variable for all groups

Assumption on the normality of Arousal

The Shapiro-Wilk test for normality assumption indicated at a 5% significance level, the normality assumption for three of the four groups defined by the two levels of each factor was not confirmed, except for one group « Textual Utilitarian search» which was normally distributed (Table 14, Figure 16).

Test of Normality for Arousal								
Hypothesis	Search Method	Search Object	Kolmogorov-Smirnova			Shapiro-Wilk		
			Statistic	df	Sig.	Statistic	df	Sig.
H2	Visual	Hedonic	.198	17	.076	.899	17	.064
		Utilitarian	.191	16	.124	.878	16	.036
H5	Textual	Hedonic	.319	16	<.001	.858	16	.018
		Utilitarian	.149	17	.200*	.951	17	.479
*. This is a lower bound of the true significance.								
a. Lilliefors Significance Correction								

Table 14 - Normality verification for arousal

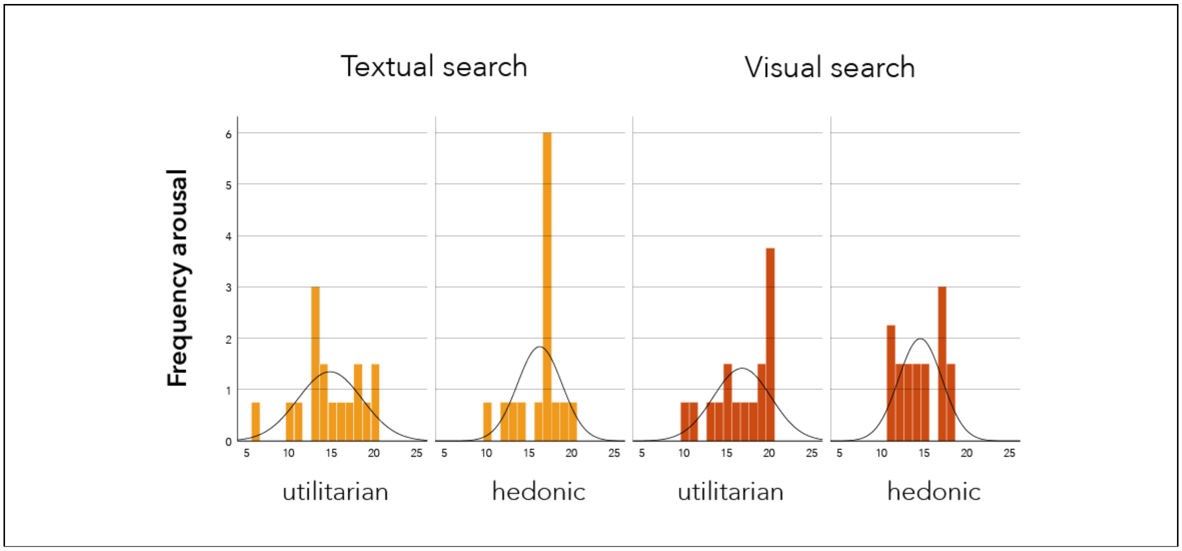

Figure 16 - Frequency curves for arousal variable for all groups

Assumption on the variance of Arousal

The evaluate the equality of variance, Levene's Test at a 5% significance level was used. The assumption of the equality of variances across the four groups was defined by the two levels of each factor and was not rejected by the Levene test based on the mean (Table 15). The Assumption on Variance of Dominance was satisfied for all four groups.

Levene's Test of Equality of Error Variances[a,b]					
		Levene Statistic	**df1**	**df2**	**Sig.**
Arousal	Based on Mean	1.405	3	62	.250
	Based on Median	1.547	3	62	.211
	Based on Median and with adjusted df	1.547	3	54.179	.213
	Based on trimmed mean	1.451	3	62	.237
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.a,b					
a. Dependent variable: arousal					
b. Design: Intercept + Search Type + Search Object + Search Type x Search Object					

Table 15 - Variances verification for arousal

Appendix 3

Descriptive Statistics for Dominance								
Hypothesis	Search Method	Search Object	N	Std. Deviation	Mean	Median	Min. on /20	Max. on /20
H3	Visual	Hedonic	17	4.030	13.35	13.00	6	20
		Utilitarian	16	2.729	16.88	17.00	11	20
H6	Textual	Hedonic	16	2.387	16.31	16.50	11	20
		Utilitarian	17	4.039	15.76	17.00	5	20

Table 9 - Mean, median scores, and standard deviation for Dominance as shown on p.42

Textual search gets higher scores than visual search. The dispersion of visual search is higher than the dispersion of textual search. One case has been returned as an outlier for textual search, at the bottom of the distribution (Figure 17). Scores for utilitarian objects are higher and less dispersed than scores for hedonic objects. For the utilitarian object, only one score (out of 33) is an outlier, at the bottom of the distribution. No case has been returned as an outlier for hedonic objects (Figure 17).

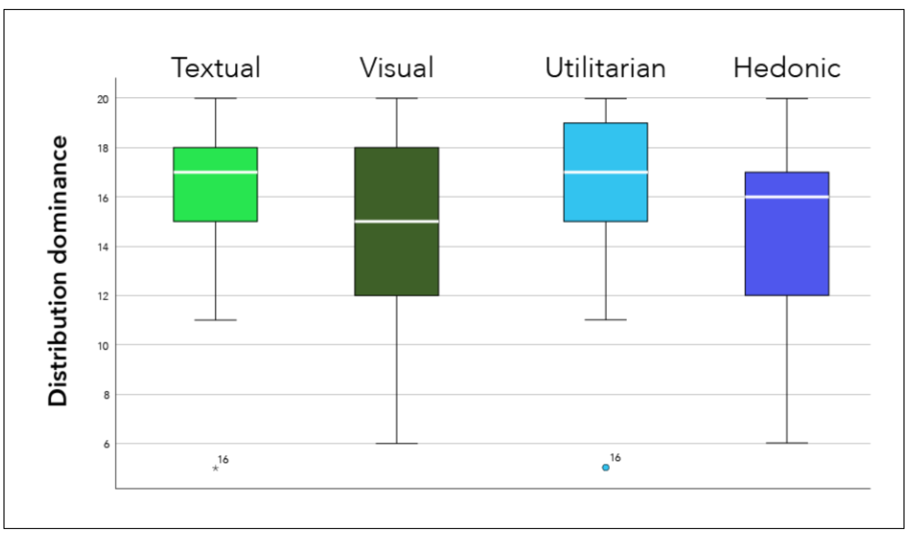

Figure 17 - Distribution curves for dominance variable for all groups

Assumption on the normality of Dominance

The Shapiro-Wilk test for the normality assumption at a 5% significance level was performed. The normality assumption for the four groups, defined by the two levels of each factor, was not rejected, except for one group «Textual search and Utilitarian motivations». (Table 16, Figure 18). The assumption of normality of dominance was satisfied for three of the four groups, the exception being the group «Textual search and Utilitarian motivations».

Test of Normality for Dominance								
Hypothesis	Search Method	Search Object	Kolmogorov-Smirnova			Shapiro-Wilk		
			Statistic	df	Sig.	Statistic	df	Sig.
H3	Visual	Hedonic	.102	17	.200*	.974	17	.889
		Utilitarian	.157	16	.200*	.914	16	.135
H6	Textual	Hedonic	.135	16	.200*	.960	16	.668
		Utilitarian	.208	17	.048	.875	17	.026
*. This is a lower bound of the true significance.								
a. Lilliefors Significance Correction								

Table 16 - Normality verification for dominance

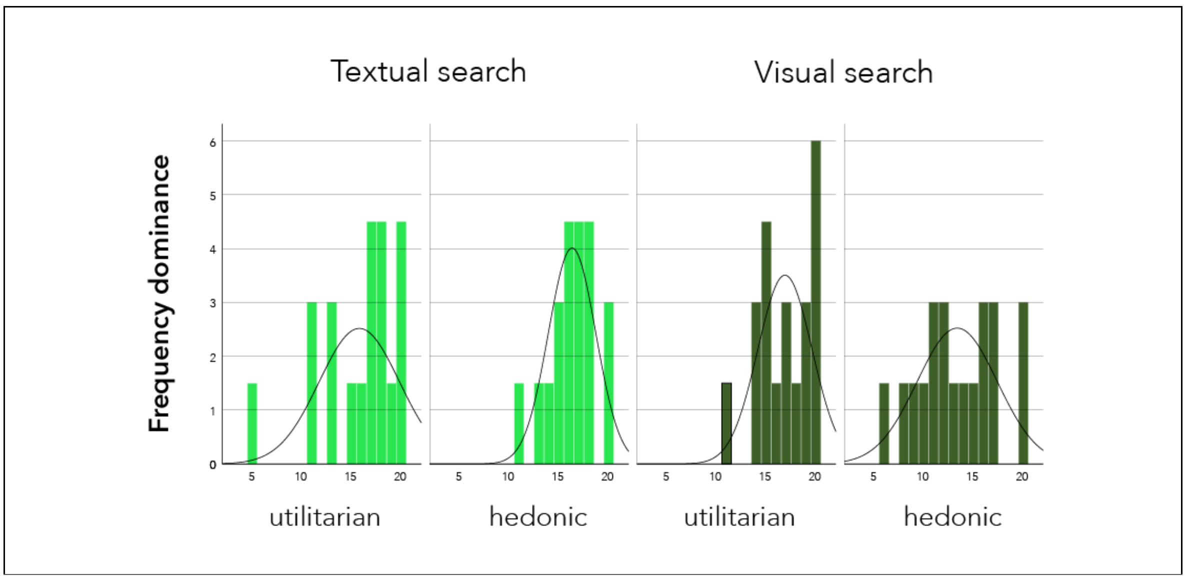

Figure 18 - Frequency curves for dominance variable for all groups

Assumption on the variance of Dominance

The Levene's Test of Equality of error variances at a 5% significance level was performed. The assumption of equality of variances across the four groups, defined by the two levels of each factor, was not rejected by the Levene test based on the mean (Table 17).

Levene's Test of Equality of Error Variances[a,b]					
		Levene Statistic	df1	df2	Sig.
Dominance	Based on Mean	2.242	3	62	.092
	Based on Median	1.536	3	62	.214
	Based on Median and with adjusted df	1.536	3	44.940	.218
	Based on trimmed mean	2.021	3	62	.120
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.a,b					
a. Dependent variable: dominance					
b. Design: Intercept + Search Type + Search Object + Search Type x Search Object					

Table 17 - Variances verification for dominance

Appendix 4

Original quotations

« Visuelle était compliquée, on sentait coincée avec les options, C'était super facile mais pour d'autres j'ai pas trouvé le backsplash, pas trouvé le comptoir, ça sortait quelquechose d'autres. Oui c'était plus demandant, pas pratique. C'est mieux d'allez au shopping et taper le texte. C'est plus ardu de prendre en photo et télécharger. Visuelle était plus demandant avec moins d'options. »	Visual search, was complicated, more demanding, and not practical, so much so that they would have preferred to physically go to the store or perform a textual search. Taking a picture of the object added to the aggravation and laboriousness. The small amount of options made them feel stuck with such results. p.46
« La recherche visuelle au début, pas le 1er réflexe de comprendre, c'est le fun, l'élément visuelle y a une p'tite adaptation, complexité, pis pas au Québec, ça emmène beaucoup à l'international. »	Visual search was fun but more demanding because it required some adaptation for the search which added complexity to the task, in addition, the results of the product often came from international big box stores and not Québec's merchants. p.47
« C'était très agréable plus précis, plus cohérent, plus de fois des choix réaliste, plus lié à avoir au Québec. versus. image c'était à l'international. »	The textual search results were precise, targeted, and coherent, these factors made them feel confident in the search results. p.47
« Visuelle était pas stimulant, rapide mais pas de satisfaction, le processus de recherche. Visuelle moins stimulant mais efficace, le produit – photo – rapide en bas, et trop de bouton similaires. C'est précis, c'est bien, mais c'est limitant, si on veut être inspirée. »	Visual search was less stimulating yet efficient, it was limiting if you wanted to be inspired. The search depended on the end goal and found visual search practical. p.49
« Texte plus de possibilité de guider la recherche. Être plus précis pour diriger la recherche. Il faut savoir ce que tu recherche, faut préciser pour recherche visuelle : y a pas de liberté, c'est imposé».	Offered a greater opportunity to guide the search, to be more precise and directive. Whereas the visual search had no freedom to choose, the results were imposed. p.49
« Visuelle frustrant en premier, c'était différent, sur Google Canada la planche... le comptoir, les tuiles ça sortait des grilles, c'était moins efficace. »	Visual search was frustrating, from the start on Google Canada results for the countertop and backsplash resulted in grills, it was less efficient. P.52

« La reconnaissance tout de suite, il te propose des produits, mais faut bien regarder, bien faire attention à ce que t'as pris ou similaire dans les détails qui ne corresponent pas, est-ce c'est standard un professionel saurait le choisir. »	It recognized the object immediately, however within the proposed results, you have to look carefully and pay close attention because even when it is similar, the details don't match up. A professional would be able to tell the difference. p.52
« Visuelle facile, pour trouver le produit exact, ça sort directement le même produit que l'image, ce que l'on veut. Pour textuelle beaucoup de produit, textuelle avait plus de choix, il fallait écrire et spécifier ce qu'on veut. »	Visual was best suited to find the exact product, it output the exact match as the input image. Whereas textual search offered a variety of products and more choices. You just needed to specify what you wanted. p.52
« Textuelle plus de choix, large gamme plus de prototype. Visuelle plus précis, uniforme priver les autres opportunités, privé du extra features ou des fonctions extras. »	Visual search was more precise and uniform, denying the searcher from any variations from the item, or any extra features and functionalities. p53
« Les mots clé permettait de chercher en profondeur, plus de diversité. Pour visuelle on a rapidement un résultat mais on peut pas mettre de texte ce qui est limitant. »	There was more control with textual searches, which enabled deeper searches and diverse results. Sure, a visual search was quick when you wanted the exact match. p.54

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