Click-Click-Add – Product Search Strategies in Online Shopping

ABSTRACT

People shopping online often abandon their shopping sessions because they feel overwhelmed or insufficiently supported during product searches. This highlights a need to better understand user behavior in order to design more helpful and satisfying e-commerce experiences. We instructed 31 participants to perform two goal-directed product searches online, simulating real-world scenarios for two product types: search products (laptops) and experience products (jackets). Through observation and think-aloud protocols, we captured user behavior across browser tabs and online resources, enabling us to develop a novel annotation scheme for product search that captures resources used, views seen, and actions taken. Qualitative analysis of these annotated sessions revealed nine distinct product search strategies, which participants often combined and applied at different stages of their search sessions. For each strategy, we describe similarities and differences between search and experience products and identify common strategy combinations across product types. Finally, by mapping these findings to established information-seeking models, we offer insights that can inform the design of more effective and supportive e-commerce platforms.

KEYWORDS

User Behavior in E-Commerce; Consumer Information-Seeking; Search Strategies; Consumer Decision-Making; Search vs. Experience Products

INTRODUCTION

E-commerce has become a dominant force in the global retail landscape, representing over 17% of global retail sales in 2024. Transactions exceeded seven trillion US dollars in 2024, with projections indicating continued expansion to an anticipated revenue of 10.4 trillion US dollars by 2029 (Statista, n.d.). Among product categories, fashion and electronics dominate, with each segment generating over one trillion US dollars globally in 2024 (eCommerceDB, n.d.).

Despite extensive commercial development and scholarly investigation, product search remains challenging for consumers. Shoppers face a vast array of available options and are confronted with large amounts of product-related information (Akalamkam & Mitra, 2018). Consequently, consumers may experience information and choice overload, inducing feelings of stress and frustration in users (Kusi, Rumki, Quarcoo, Otchere, & Fu, 2022) and decreasing their motivation to make a purchase decision (Iyengar & Lepper, 2000; Scheibehenne, Greifeneder, & Todd, 2010). Moreover, customers often do not feel adequately supported by customer service during their search (Kanaan et al., 2023). Feeling overwhelmed, they are more likely to abandon their shopping carts (Das Sarma, Sarkar, & Sarkar, 2025; Jiang, Zhang, & Wang, 2021), contributing to the persistently high online shopping cart abandonment rate of around 70% (Baymard Institute, n.d.; Snyder, 2024). Additional complexities arise from different product types: While *search products* can be more easily evaluated before purchase (e.g., through technical specifications), *experience products* typically demand usage or trial to properly evaluate their quality (P. Huang, Lurie, & Mitra, 2009; Basu, 2018; Korgaonkar, Silverblatt, & Girard, 2006).

Previous research introduced process models for both general web search (Choo, Detlor, & Turnbull, 2000) and online shopping (Shah & Paul, 2020; Karimi, Papamichail, & Holland, 2015), and identified a variety of search strategies in these domains (Hawk & Wang, 1999; Thatcher, 2008; Rowley, 2000; Bhavnani, 2001). However, much of this work has either concentrated on specific user characteristics (e.g., domain expertise (Bhavnani, 2001; Thatcher, 2008)) or particular aspects of the search process (e.g., query refinement and expansion (Rowley, 2000)). Moreover, a critical distinction exists between general web search and product search: whereas the former often involves seeking unstructured or semi-structured information in documents or websites, the latter typically aims to locate a single product entity characterized by structured data (e.g., specifications) (Nie, Wen, & Ma, 2007; Pham, Rizzolo, Small, Chang, & Roth, 2010). Hence, caution is warranted when generalizing findings from web search to product search.

Building upon the identified gap, our research investigates general behavioral search strategies specifically within the realm of online product search, analyzing user behavior across multiple browser tabs regardless of their expertise level. We conducted an observational user study with 31 participants simulating real-world search scenarios for laptops (representative of search products) and jackets (representative of experience products), documenting user behaviors through screen recordings and think-aloud protocols.

Our research is guided by the following research questions:
RQ1: What behavioral strategies do consumers employ during online product search?
RQ2: How do these behavioral strategies align with existing models for information-seeking and decision-making in general web search and online shopping?

During our analysis, we developed a comprehensive annotation scheme that spans resources used, views seen, and actions taken. Based on the annotated search sessions, we identified nine distinct behavioral product search strategies utilized when searching for both search and experience products. These strategies characterize navigation patterns, product comparison methodologies, and approaches to supplementary information acquisition. Building on these insights, we have situated the identified behavioral search strategies within existing models of information-seeking behavior.

Collectively, our findings provide an enhanced understanding of users' behavioral patterns during online product search. The identified strategies offer a foundation for improving user support throughout the online shopping journey.

RELATED WORK

As web access and e-commerce continue to evolve and grow in relevance, researchers have sought to understand the behaviors and decision-making processes that shape users' web search and online shopping experiences. This section synthesizes relevant theoretical frameworks and empirical findings from the fields of information science, business and marketing, and interactive information retrieval. It covers crucial areas such as information-seeking and decision-making models, product classification, as well as search tactics and strategies, all of which contribute to our understanding of online consumer interactions.

Information-Seeking and Decision-Making in e-Commerce

Understanding users and modeling their behavior during information-seeking has been the focus of research for decades. One of the fundamental models is Ellis' information-seeking model (Ellis, 1989; Ellis, Cox, & Hall, 1993; Ellis & Haugan, 1997). His information-seeking stages have been used as a framework to describe generic characteristics of information-seeking behavior, online and offline. It originates from the description of the information-seeking behavior of social scientists and researchers from other domains looking for scientific literature (Ellis, 1989; Ellis et al., 1993; Ellis & Haugan, 1997). It originally contained seven stages: (1) starting, (2) chaining, (3) browsing, (4) differentiating, (5) monitoring, (6) extracting, and (7) verifying. On the basis of log data, questionnaires, and interviews with knowledge workers, Choo et al. (Choo et al., 2000) later adapted this model (stages 1-6) to web contexts to describe information-seeking among professionals online.

Through a survey with online shoppers, Shah and Paul (Shah & Paul, 2020) tested the applicability of Ellis' model for online shopping and found that only three stages (starting, monitoring, and verifying) proved valid and reliable. Karimi et al. (Karimi et al., 2015) observed users during two online purchasing tasks and proposed an iterative six-stage decision-making process model for online shopping. It includes (1) need recognition, (2) formulation of criteria, (3) information gathering, (4) evaluation of options, (5) appraisal, and finally, (6) purchase. For online shopping contexts, this model includes two important steps, "evaluation" and "choice", which are not represented in Ellis' original model.

Search Strategies in Online Information-Seeking

In the analysis of information-seeking behavior, prior research consistently differentiates between search tactics and search strategies. Tactics are usually described on a basis of single actions such as reformulating a query or organizing search results, while strategies comprise several tactics and therefore represent search behavior at a more abstract level (Bates, 1979; Marchionini, 1995; Xie & Joo, 2010; He, Qvarfordt, Halvey, & Golovchinsky, 2016). In our study, we are focused on the latter, analyzing behavioral patterns that consist of multiple actions.

Several researchers have investigated online search strategies. In an early study investigating general web search behaviors, Hawk and Wang (Hawk & Wang, 1999) analyzed logs, screen recordings, and think-aloud recordings of 24 participants, each performing two search tasks. Through qualitative analysis of the captured data, they developed a coding scheme that allowed them to identify ten recurring problem-solving strategies (e.g., "double-checking" and "shortcut-seeking") that users employed during their searches.

Thatcher (Thatcher, 2008) later explored how web experience influenced search approaches. Analyzing clickstream data, verbal protocols, and performance measures from 80 participants, he identified 12 search strategies. Notably, experienced users tended to employ more sophisticated strategies, such as the "Parallel Hub-and-Spoke" strategy involving the parallel opening of multiple browser tabs from a search results page for comparison. In contrast, less experienced users were more likely to use less cognitively demanding strategies like "Link-Dependent", relying solely on hyperlinks within websites.

In the context of e-commerce, Rowley (Rowley, 2000), drawing on consumer behavior literature, defined four search strategies, primarily focusing on how consumers refine and expand their search queries: "Briefsearch" (quick initial search), "Building blocks" (breaking down queries, exploring terms), "Successive fractions" (starting broad, then narrowing), and "Citation pearl-growing" (using initial sources to find terms for subsequent searches).

Bhavnani (Bhavnani, 2001) observed healthcare and online shopping experts performing search tasks both within and outside their expertise while thinking aloud. He found that online shopping experts searching for a digital camera tended to follow a "review-compare-discount" sequence during their search. This strategic behavior was less evident when experts searched outside their domain.

Building upon these insights into online search strategies, our current research distinguishes itself in several key aspects. Hawk and Wang's and Thatcher's work offer an understanding of general web search strategies across various tasks, whereas our focus is specifically on the nuances of online product search. Furthermore, Rowley's strategies are primarily concerned with query formulation and refinement within an e-commerce context, while we aim to examine more general behavioral patterns during product search. Finally, Bhavnani's study concentrates on the search strategies employed by domain experts, whereas our work seeks to identify strategies across expertise levels.

Search vs. Experience Products

Consumer search behavior is influenced by product type. Nelson (Nelson, 1970) distinguished between *search products*, evaluable via pre-purchase information, and *experience products*, requiring actual use for quality assessment. Laband (Laband, 1991) proposed these two product types as endpoints on a continuum, with most products positioned somewhere in between. Perfume exemplifies an experience product due to its subjective and sensory evaluation criteria. Conversely, standardized and utilitarian products such as airplane tickets are better understood as search products, since their key attributes can be easily assessed before purchase (Weathers & Makienko, 2006; Girard & Dion, 2010; Korgaonkar et al., 2006).

In e-commerce contexts, Weathers and Makienko (Weathers & Makienko, 2006) characterized experience products as those requiring direct interaction for evaluation, while search products could be adequately judged through second-hand information. Klein (Klein, 1998) hypothesized that interactive media in online stores might create "virtual experiences", potentially transforming experience products into search products. However, Nakayama et al. (Nakayama, Sutcliffe, & Wan, 2010) found limited empirical evidence for this transformation, with personal computers representing a notable exception due to increased standardization and quality improvements. Empirical research in e-commerce settings has demonstrated that consumers seeking experience products tend to engage in more focused, in-depth searches with greater reliance on product reviews and multimedia content due to a higher perceived risk. In contrast, those searching for search products tend to conduct broader, more efficient searches, as these products' well-defined attributes facilitate straightforward comparison (P. Huang et al., 2009; Basu, 2018; Korgaonkar et al., 2006).

Our study utilizes this distinction, classifying laptops as search products and jackets as experience products, consistent with prior research (Girard, Silverblatt, & Korgaonkar, 2002; Korgaonkar et al., 2006; Luan, Yao, Zhao, & Liu, 2016; Weathers & Makienko, 2006).

OBSERVATIONAL USER STUDY

To investigate how consumers search for products online, we conducted a remote user study, observing 31 participants in a natural environment while they searched for two products online. We used a qualitative approach, observing their behavior while they thought aloud during the search tasks. The user studies were performed between the 17th June and 18th July 2024. Prior to this, our institute's ethics committee gave ethical clearance for the study setup.

Procedure and Tasks

The study moderator (first author of this paper) guided the participants through the process via Microsoft Teams. We recorded the audio of the session and the participant's screen via Teams' screen sharing feature. To ensure anonymity, participants were instructed to change their display names and to turn off their cameras for the study.

The study started with an online questionnaire hosted on SoSci Survey. Participants first provided informed consent and completed a demographic survey, providing information on their age and gender. Subsequently, each participant completed two search tasks in counterbalanced order: Searching for a new laptop and searching for a new jacket. Each task started with a scenario description:

Laptop: *"Your laptop has broken down. Now you're looking for a new one online."*

Jacket: *"You have lost your favorite jacket. Now you're looking for a replacement online."*

After receiving each scenario, participants were instructed to begin their search by opening a new tab in their currently open browser, with the freedom to browse the web without restrictions. To prevent participants from feeling rushed, no time limit was mentioned beforehand. The study moderator also clarified that our focus was on their search process rather than their ability to quickly find a suitable product. However, the moderator ended the search session if a suitable product was not found within 15 minutes. Participants were instructed to think aloud (Someren, Barnard, & Sandberg, 1994), verbalizing their thoughts, actions, and goals throughout the search process.

Participants

We recruited 31 participants (15 male, 16 female) on the online crowdsourcing UK-based platform Prolific. The participants ranged in age from 18 to 47 years (M=30; SD=9), were required to be fluent in English, and represented a diverse set of nationalities, including Italy, South Africa, Turkey, Poland, the USA, the UK, Nigeria, Canada, Brazil, India, Serbia, Zimbabwe, and France. Each participant was compensated £7.50 via the Prolific platform, with an average completion time of approximately 33 minutes (M=33:19 min; SD=13:58 min), resulting in an hourly rate of roughly £13.64.

Most participants engaged actively in the search tasks. However, a few participants finished their search very quickly, which raised doubts about the representativeness of their search behavior. We therefore excluded searches in which only one product page was viewed and where participants executed less than five interaction steps (e.g., formulating queries, clicking links, or applying filters), as we expect these behaviors to signal limited engagement. Following these exclusions, the final dataset included 25 search sessions for laptops and 23 for jackets.

Behavior Annotation

We developed an annotation scheme for the screen recordings based on the *Model Human Behavior* (Card, 1981), which defines three human processing units: cognitive, perceptual, and motor. Adapting these units to our context, we established three categories: *resources*, *views*, and *actions*. We define *resources* as the results of cognitive evaluations, goals, and intentions, following Norman's seven stages of user activities (Norman, 1986). *Views* correspond to the type of page and content users engage with, incorporating both perceptual and cognitive elements. Lastly, *actions* represent motor behaviors, i.e., clicks and keystrokes. In addition to these three categories, we annotated the index of the tab on which each interaction step occurred, including instances when a tab was closed during an interaction step.

Altogether, we annotated 1,768 interaction steps regarding resources used, views seen, and actions taken. In the laptop scenario, participants on average viewed 4.3 products (SD=2.4) and performed 33.2 interaction steps (SD=25.1), while in the jacket scenario, they viewed 5.9 products (SD=4.3) and performed 40.7 interaction steps (SD=27.7). 18 participants (72%) decided on a laptop, while another 18 (78%) chose a jacket within the allotted 15 minutes.

To determine the code set per category (*resources*, *views*, and *actions*), all authors annotated four search sessions (two laptops, two jackets) and added possible codes to a code pool. This code set was refined in two workshops with all four annotators until a final consensus was reached. All annotators validated the final annotation scheme on data from two more search sessions. Table 1 shows the final code set for all three categories together with the codes' relative frequencies across both product types.

To assess inter-rater agreement, we calculated Krippendorff's alpha. A research assistant annotated one randomly selected search session from each of the four annotators. To minimize bias due to varying search session lengths, annotations for the assessment were limited to the first 32 interaction steps per product type, which reflected the average number of steps across all participants. The resulting Krippendorff's alpha was 0.87, indicating good agreement (Krippendorff, 2019).

The annotations yielded a representation of each search session through standardized *resources*, *views*, and *actions* codes, enabling comparisons of individual patterns across participants. We converted each participant's annotated search sessions into visual representations to identify distinct behavioral search strategies. We focused on the most frequently used resources, views, and actions, creating interaction diagrams similar to the one shown in Figure 1. In these diagrams, interaction steps are visualized along the x-axis while open browser tabs appear along the y-axis. Resources and views were color-coded, and actions were labeled as needed. The diagrams we used for strategy identification included more detailed actions than the version shown in Figure 1, which we simplified in this paper for demonstration purposes. In an additional workshop, we discussed and clustered these diagrams across product types whenever they exhibited similar behavioral patterns. Since participants often combined multiple patterns during one search session, a single diagram could belong to multiple clusters. Finally, we labeled the resulting clusters, arriving at nine distinct behavioral strategies for product search. Employing these nine labels, two authors assigned all relevant strategies to each diagram and then reached a consensus on the labels for each diagram.

Resource	**[%]**
multibrand (shop, e.g., Amazon)	45.9
singlebrand (shop, e.g., Apple)	28.5
search engine: all (default results page tab)	11.7
search engine: start page	6.2
secondhand/refurbished (shop, e.g., ebay)	2.0
social media (e.g., YouTube, Instagram, Reddit)	1.5
search engine: products/shopping tab	1.2
meta-multibrand (e.g., price comparison or discount sites)	1.1
expert editorials/blogs	1.1
search engine: videos tab	0.6
search engine: images tab	0.1

View	**[%]**
results page	37.7
product page	37.6
homepage (search engine or online shop)	10.0
product page: images/videos (click or hover)	7.2
product page: reviews (click or hover)	2.9
editorial content	1.6
comparison page	1.0
shopping cart/wishlist	0.7
video (outside of a product page)	0.7
profile page (in social media)	0.5
results page: further information (featured snippets in Google)	0.1

Action	**[%]**
click to product page	17.7
filter / set facet	16.5
formulate query	15.7
configure product/choose options	11.4
back	10.6
click non-product link (on results pages)	8.8
click recommended item	5.3
reformulate query	4.8
navigate website	2.3
add to shopping cart/wishlist	1.8
filter/navigate product reviews	1.7
add to product comparison	1.0
sort results	0.8
sort product reviews	0.7
click to open cart	0.6
remove from shopping cart/wishlist	0.3

Table 1. Codes and Their Relative Frequencies for *Resources*, *Views*, and *Actions*

BEHAVIORAL STRATEGIES DURING PRODUCT SEARCH

This section presents the nine distinct behavioral strategies for product search we identified by qualitatively clustering similar patterns in 48 annotated search sessions (addressing **RQ1**), discussing them in relation to prior research. Importantly, they are not mutually exclusive, as participants often employed several strategies per session. Figure 1 exemplifies a search session where participant P11 used six strategies, while Table 4 shows the relative strategy frequencies across laptop and jacket searches.

Behavioral Strategy 1: Funneling

The *funneling* strategy involves narrowing the search space through filters, facets, sorting functions, and query reformulations. This behavior allows product searchers to progressively refine results to match specific criteria. At the product level, funneling often includes configuring attributes such as color, size, and other customizable options. In our study, 17 participants (68%) employed the funneling strategy when shopping for laptops, while 21 participants (91%) did so when shopping for jackets, making it a particularly prominent behavior. Funneling was typically implemented directly within web shops through categorical and numerical filters from menus, side facets, and prepared filter links. Figure 1 illustrates how P11 applied funneling in interaction steps 56-58 by setting filters on an online shop's results page.

From a theoretical standpoint, funneling is related to the "formulation of criteria" stage in Karimi et al.'s (Karimi et al., 2015) decision-making process model for online shopping. It represents non-compensatory decision-making, specifically "elimination-by-aspects", in which any option failing to meet a given threshold for certain attributes is discarded without further consideration of its other features (Song, Jones, & Gudigantala, 2007).

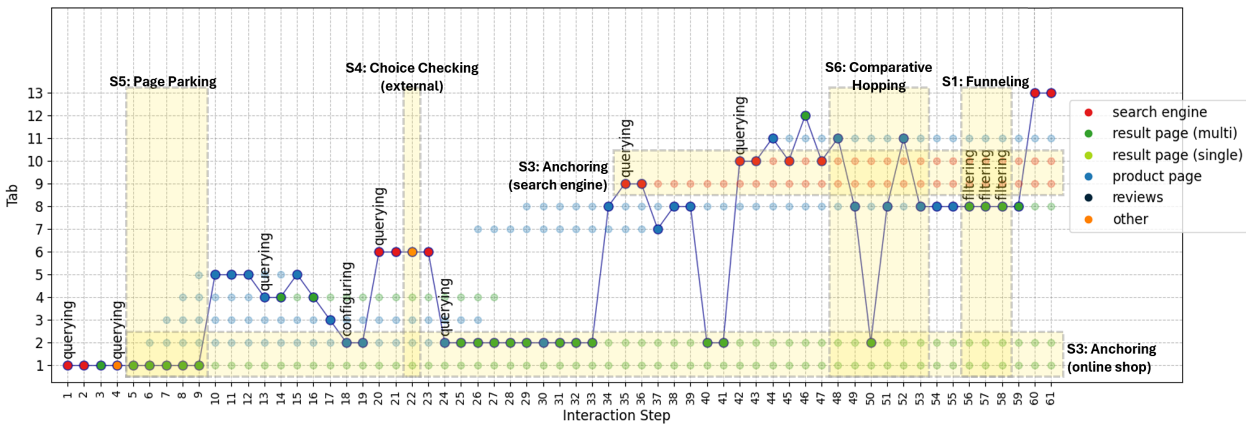

Figure 1. Interaction Diagram for P11 (Laptop Search) with Color-coded Resources and Views, Annotated User Actions, and Identified Search Strategies Highlighted in Yellow. Opaque Dots Represent Active Tabs, While Translucent Dots Indicate Inactive Tabs

Behavioral Strategy 2: Scoping

We define *scoping* as consumers' choice of a search environment—either predominantly relying on web search engines to navigate directly to product pages across multiple shops, or primarily using the built-in search and navigation tools within a single online shop. In effect, users are deciding the breadth of their search space. Participants in our study applied scoping in 12 (48%) of the laptop search sessions, with 6 (24%) participants primarily relying on web search engines and another 6 focusing on online shops. For jacket searches, 11 (48%) participants exhibited a clear search scope, with 4 (17%) mainly using web search engines, compared to 7 (30%) primarily searching within online shops.

The distribution of web versus online shop scoping for both product types may stem from inherent differences in their attributes. Laptops, with more standardized characteristics (e.g., screen size or processor type), facilitate comparisons in a broader web search environment. Conversely, the more subjective aspects relevant to jackets (e.g., fit, feel, and design) might steer shoppers toward online shops offering curated selections with familiar styles, fits, and fabrics.

Participants' utterances during their search sessions revealed further insights into scoping. Cognitive heuristics helped participants to narrow their search (i.e., set the scope) in both search engines and online shops: The availability heuristic (Tversky & Kahneman, 1974) drove participants to shops and brands readily accessible in memory (P22: *"I choose Amazon [...] [b]ecause it's famous"*); familiarity (Zajonc, 2001; Samuelson & Zeckhauser, 1988) and loyalty (Jacoby & Kyner, 1973) steered them to shops or brands they had prior experience with (P31: *"I have some of their clothes, so I'm used to their cut and the fabrics."*); and the representativeness heuristic (Tversky & Kahneman, 1974) led participants to favor certain products because they associated a brand with attributes such as quality or trustworthiness (P26: *"[W]henever it comes to electronics, I make sure the brand is having a reputation."*). The application of heuristics to reduce search effort aligns with *information foraging theory* (Pirolli & Card, 1999), which posits that searchers aim to maximize their information gain while minimizing the cost of searching.

Behavioral Strategy 3: Search Anchoring

The *search anchoring* strategy involves keeping either a search engine results page (SERP anchoring) or an online shop results page (online shop anchoring) open throughout multiple interaction steps. This page serves as a base to which searchers can return to reformulate queries or revisit result lists. During laptop searches, 11 (44%) participants employed one of the two types of search anchoring, compared to 14 (61%) in jacket searches. Across participants, online shop anchoring was more prevalent in jacket searches (8 participants, 35%) than in laptop searches (6 participants, 24%), while search engine anchoring was observed at a similar frequency for both product types (5 (25%) participants in the laptop search and 6 (26%) participants in the jacket search). Figure 1 shows how P11 anchored their search both on two online shop results pages (interaction steps 5-61) and on two SERPs (interaction steps 35-61).

For consumers who anchor their search on results pages, it is critical that online shops provide users with strong *information scent* (e.g., clear images, descriptive titles, and prominent star ratings) (Pirolli & Card, 1999). For example, recommendations with images at top of a SERP facilitates consumers' relevance assessment for options before navigating to the product page. In our study, horizontal recommendations at the top of the SERP accounted for 14.5% of clicks performed on the default tab of SERPs during laptop searches and even 26.4% during jacket searches.

Behavioral Strategy 4: Choice Checking

Choice checking refers to gathering of third-party information during product searches, either by consulting customer reviews on product pages within online shops or seeking external sources such as expert editorials, blogs, or social media. In our study, 14 (56%) participants engaged in choice checking while searching for laptops: 8 (32%) consulted customer reviews and 6 (24%) gathered external information, with two participants doing both. For jacket searches, 10 (43%) participants applied choice checking, predominantly by reading customer reviews (9 participants, 39%) rather than external sources (1 participant, 4%), with one participant consulting both. P11 applied choice checking by seeking information from an expert editorial (see Figure 1, interaction step 22).

The more frequent consultation of customer reviews on product pages for jackets (i.e., the *experience product*) compared to laptops (i.e., the *search product*) aligns with previous empirical findings (P. Huang et al., 2009). However, our observations also reveal a notable difference in the gathering of external information, a dimension that warrants further investigation. It is plausible that the enhanced financial risk and diverse technical attributes associated with laptops motivate consumers to seek additional technical information and (expert) opinions that are perceived as more objective (P30: *"People [writing reviews] on [a discount] site are trustworthy [...] because there's no marketing."*; P3: *"You don't know if it's AI bots leaving reviews [on a product page]."*). Consequently, online shops might consider integrating tailored types of information into product pages based on the product type. Overall, the prevalence of the choice checking strategy underscores the importance of verification in online shopping, as identified by Shah and Paul (Shah & Paul, 2020), and aligns with the "information gathering" stage in Karimi et al.'s (Karimi et al., 2015) decision-making process model for online shopping.

Behavioral Strategy 5: Page Parking

In *page parking*, consumers identify a results page from which they rapidly open multiple promising links in new tabs, without necessarily visiting all these tabs immediately. For instance, when encountering a results page with several relevant products, the consumer might scan the page and open all interesting options in new tabs for later examination. Thus, the original results page functions as a parent node from which multiple child nodes originate, "parked" for subsequent investigation. This strategy appeared in 9 (36%) laptop search sessions and 6 (26%) jacket search sessions. We borrow the name of this strategy from the Nielsen Norman Group, who explained page parking in a blog post (Nielsen & Moran, 2015). P11 employed page parking in interaction steps 5-9, opening product pages as inactive browser tabs on an online shop search results page (see Figure 1).

The page parking strategy is related to "tabbed browsing", a common behavior in general web search, where users open multiple tabs for parallel tasks, comparisons, and quick page revisits, reducing back button usage (Aula, Jhaveri, & Käki, 2005; Weinreich, Obendorf, Herder, & Mayer, 2006; Dubroy & Balakrishnan, 2010). The specific behavior of opening multiple search results in new tabs or browser windows was identified as "branching" in general web search by Huang et al. (J. Huang, Lin, & White, 2012) and "Parallel Hub-and-Spoke" during online shopping by Thatcher (Thatcher, 2008)).

The use of digital tools to augment human cognition (e.g., setting reminders or using calculators) has been described in the literature as a form of *cognitive offloading* (Risko & Gilbert, 2016). In the context of page parking, inactive tabs serve as an external short-term memory, allowing users to temporarily store relevant options and free up cognitive capacity for tasks such as product comparisons. Online shops should facilitate this behavior on both desktop and mobile devices. Additionally, designers should account for the limited space in desktop browser tab bars by crafting favicons and title tags that provide clear informational value and effectively differentiate their store (Nielsen & Moran, 2015). Looking ahead, AI-enabled assistants might reduce users' need to open multiple tabs by autonomously retrieving information from relevant product pages across various online shops.

Behavioral Strategy 6: Comparative Hopping

Comparative hopping refers to the rapid switching between product pages in different tabs in consecutive interaction steps, allowing consumers to directly compare product data. We observed this behavior in 6 (24%) laptop searches and 9 (39%) jacket searches. Figure 1 shows that P11 engaged in comparative hopping between interaction steps 48 and 53.

In contrast to the *funneling* strategy, in which non-compensatory decision-making aids the formation of an initial consideration set, comparative hopping reflects a later stage in consumers' decision-making process where users evaluate pre-filtered options, analyzing trade-offs and weighing various product attributes in greater depth (Häubl & Trifts, 2000). To support this evaluative phase, search engines and online shops could integrate dedicated tools such as plugins that automatically generate side-by-side comparison tables, enhanced with visual cues, AI-generated comparative summaries, and integrated customer reviews to further highlight distinct differences between selected options.

Behavioral Strategy 7: Minimalist Searching

Minimalist searches are brief sessions in which consumers quickly arrive at a purchase decision with minimal interaction. These searches involve a straightforward progression from an initial query on a search engine or online shop to the selection of a product deemed satisfactory. Consumers employing this strategy perform limited filtering, querying, or product configuration, often considering only a few options. In our study, minimalist searching was observed in 9 (36%) laptop sessions and 6 (26%) jacket sessions. Participants using this strategy viewed an average of 2.1 products and executed 10.7 interaction steps, compared to overall averages of 5.0 products and 36.8 steps.

Several factors may drive minimalist searching behavior. First, users might have a clear search target in mind—a phenomenon Su et al. (Su, He, Liu, Zhang, & Ma, 2018) identified as "Target Finding" intent in mobile online shoppers. Second, such behavior may indicate a *satisficing* approach, where users settle for an option that is "good enough" rather than seeking the optimal choice (Schwartz et al., 2002). Minimalist searching may be even more pronounced in satisficers with high product knowledge (Karimi et al., 2015). Third, minimalist searching might partly stem from the experimental conditions, where the simulated tasks and absence of real financial risk could have reduced participants' motivation for extensive exploration.

Behavioral Strategy 8: Single-Tab Searching

Single-tab searching involves conducting the entire search process sequentially within a single browser tab. Consumers using this strategy navigate through search engines, online shops, and product pages in a linear fashion, relying primarily on forward and backward navigation. We observed this behavior in 6 (24%) participants during laptop searches and 4 (17%) during jacket searches. These users examined fewer products (an average of 3.5, compared to the overall average of 5.0) and executed fewer interaction steps (20.7 steps versus 36.8 overall), suggesting that they explore a more limited portion of the available product landscape.

The single-tab searching behavior might stem from factors such as limited technical literacy, device constraints (e.g., smaller screens), or simply a preference for a straightforward, linear navigation process. By providing navigational elements such as breadcrumbs (a navigational aid that displays the user's current location within the site hierarchy) and allowing users to "pin" certain products or search results lists, online shops can help single-tab searchers maintain orientation and re-access key information more easily.

Behavioral Strategy 9: Product-to-Product Chasing

Product-to-product chasing is characterized by consumers opening multiple product pages consecutively without returning to or navigating to a results page in between. This behavior was observed in 2 participants (12%) during laptop searches and 5 participants (22%) during jacket searches. In all cases, this navigation pattern was facilitated by recommended items displayed directly on product pages.

This strategy is similar to the "Link-Dependent" strategy defined by Thatcher (Thatcher, 2008), which he characterized as navigating a website solely through hyperlinks instead of entering web search queries, which demands less cognitive effort. Online shops can effectively support this behavior by providing personalized recommendations on product pages.

COMBINATION OF STRATEGIES ACROSS PRODUCT TYPES

Participants typically employed multiple behavioral strategies in combination, with an average of 3.48 strategies per search session (SD=1.24). Most commonly, participants used either three or four strategies (14 (29%) participants each), while 8 participants (16.7%) used five strategies, 7 participants (14.6%) used two strategies, and few relied on just one strategy (3 participants, 6%) or as many as six strategies (2 participants, 4%) during one search session. Only three strategies (funneling, minimalist searching, and single-tab searching) were once used as the sole strategy in a search session.

Certain strategies frequently occurred together (see Table 2 for an overview). Given that funneling was used by most participants in both the laptop and jacket searches (68% and 91%, respectively), it naturally had high co-occurrence rates with other strategies such as search anchoring, page parking, and choice checking. However, several distinct patterns emerged beyond these expected co-occurrences: Both page parking and comparative hopping co-occurred with search anchoring in 12 search sessions, representing 80% of each strategy's total use. Additionally, page parking co-occurred with both comparative hopping and scoping in 10 sessions (67%). The Nielsen Norman Group refers to the behavior of quickly opening new tabs (i.e., page parking) and later comparing and analyzing them (i.e., comparative hopping) as "periods of rapid information hunting" and "periods of information digestion", attributing this two-phase separation to decreased context-switching costs for users (Nielsen & Moran, 2015; Budiu, 2019). Other notable co-occurrences included choice checking with scoping (15 sessions, 71%) and single-tab searching with minimalist searching (6 sessions, 60%).

Conversely, some strategies were mutually exclusive by definition due to their approach to browser tabs: single-tab searching and search anchoring, single-tab searching and page parking, as well as single-tab searching and comparative hopping. In addition to those, minimalist searching never co-occurred with page parking, and page parking was never used alongside product-to-product chasing.

	FUN	SCO	ANC	CHE	PAR	HOP	MIN	STS	PPC
Funneling (FUN)	–	50	58	53	37	34	18	13	16
Scoping (SCO)	**83**	–	48	**65**	44	26	17	22	13
Search Anchoring (ANC)	**96**	48	–	52	52	52	4	0	13
Choice Checking (CHE)	**95**	**71**	57	–	33	29	10	10	14
Page Parking (PAR)	**93**	**67**	**80**	47	–	**67**	0	0	0
Comparative Hopping (HOP)	**87**	40	**80**	40	**67**	–	7	0	7
Minimalist Searching (MIN)	47	27	7	13	0	7	–	40	20
Single-Tab Searching (STS)	50	50	0	20	0	0	**60**	–	20
Product-to-Product Chasing (PPC)	**86**	43	43	43	0	14	43	29	–

Table 2. Search Strategy Co-occurrence Percentages (Values ≥ 60% Marked in Bold) Across Product Types

BEHAVIORAL STAGES IN PRODUCT SEARCH

In this section, we propose a generic framework for online product search to address **RQ2**. We will map the observed "resource-view-action" combinations and identified behavioral strategies from our user study onto this overarching model.

Our framework extends the information-seeking stages introduced by Ellis (Ellis, 1989; Ellis et al., 1993; Ellis & Haugan, 1997), which–except for "verifying"–were adapted for information-seeking on the web by Choo et al. (Choo et al., 2000). While Shah and Paul's (Shah & Paul, 2020) survey-based study only found Ellis' "starting," "monitoring," and "verifying" stages to be valid and reliable in online shopping contexts, our observations challenge their findings. Specifically, we observed user behaviors corresponding to all seven stages from Ellis' original model.

To better represent the behaviors observed in our study, we integrate two stages of the decision-making process model for online shopping proposed by Karimi et al. (Karimi et al., 2015), which distinguishes an "evaluation" stage of comparing products from the final "choice" among alternatives. We further contribute a new "remembering" stage, identified through our empirical investigation, that highlights how users preserve potential purchases (e.g., via browser tabs, shopping carts, and wishlists) for later retrieval and consideration.

Synthesizing these insights, our proposed framework comprises ten stages: (1) *starting*, (2) *chaining*, (3) *browsing*, (4) *differentiating*, (5) *monitoring*, (6) *extracting*, (7) *verifying*, (8) *remembering*, (9) *evaluation*, and (10) *choice*. Table 3 provides a concise overview of these ten stages, along with exemplary online shopping activities (i.e., combinations of *resources*, *views*, and *actions*) observed in our study.

The search strategies identified in our study (see Section) can also be described by the information-seeking stages listed in Table 3. For instance, the "minimalist searching" strategy involves the stages "starting", "chaining", and "choice". Similarly, "choice checking" primarily entails the stages "extracting" (information from product pages) and "verifying" (them, e.g., via customer reviews on product pages or external expert editorials). In this way, the information-seeking stages can give insights into users' goals for each search strategy. Table 4 provides an overview of the stages associated with each strategy, as well as the relative frequency of each strategy across laptop and jacket searches.

Information-Seeking Stages	Exemplary “Resource-View-Action” Combinations
Starting (Ellis et al., 1993; Choo et al., 2000; Shah & Paul, 2020)	Opening a search engine homepage, online shop homepage, or social media (e.g., Instagram) home feed; formulating an initial query
Chaining (Ellis et al., 1993; Choo et al., 2000)	Clicking on links on SERPs or in social media; exploring the “products” tab in search engines; navigating online shops; following recommendations; navigating backwards to revisit a product
Browsing (Ellis et al., 1993; Choo et al., 2000)	Scanning results pages in search engines; scanning online shop homepages, editorial search pages, or search results lists; looking at recommendations on a SERP or in online shops
Differentiating (Ellis et al., 1993; Choo et al., 2000)	Using filters and facets to narrow down product results; sorting products by size or novelty; configuring products (e.g., by size or color); reformulating a query (e.g., to add a brand name or price range); comparing products on comparison pages; comparing prices for a product on meta-multibrand sites
Monitoring (Ellis et al., 1993; Choo et al., 2000; Shah & Paul, 2020)	Revisiting favorite shops, product pages, or social media pages
Extracting (Ellis et al., 1993; Choo et al., 2000)	Reading product descriptions and specifications on product pages; looking at images and/or videos on a product page
Verifying (Ellis et al., 1993; Shah & Paul, 2020)	Reading customer reviews on product pages; consulting expert editorials/blogs; reading through opinions about products on social media (e.g., Reddit); watching product reviews on YouTube
Remembering (observed in our study)	Opening product pages in new tabs and adding products to shopping carts/wishlists for later re-visitation
Evaluation (Karimi et al., 2015)	Comparing products in a consideration set (re-visiting product pages in inactive browser tabs; opening shopping carts/wishlists)
Choice (Karimi et al., 2015)	Deciding for or against a final product to purchase (potential addition for multi-session searches: deciding to postpone the purchase and end the current search session)

Table 3. Information-seeking Stages and Observed “resource-view-action” Combinations

	Behavioral Strategy	[%]	Associated Information-Seeking Stages
1	Funneling	79	differentiating (with filters, facets, and query reformulations)
2	Scoping	48	starting (from different scopes, search engine vs. online shop), chaining
3	Search Anchoring	48	remembering (search results) and chaining (from there)
4	Choice Checking	31	extracting and verifying (information)
5	Page Parking	31	remembering (of product pages)
6	Comparative Hopping	31	evaluation (of remembered products)
7	Minimalist Searching	31	starting, chaining, choice
8	Single-tab Searching	21	starting, chaining (forward and backward in single tab), choice checking
9	Product-to-Product Chasing	15	chaining (from product to product via recommendations)

Table 4. Product Search Strategies with Their Relative Frequencies and Information-seeking Stages

Figure 2 illustrates a prototypical product search encompassing all ten information-seeking stages from our framework: an online shopper formulates a query in a search engine (starting), follows search result links (chaining), scans a list of products on a shop site (browsing), compares products on a comparison page (differentiating), revisits favorite brand shops (monitoring), extracts information from product pages (extraction), verifies certain product attributes on external sites (verifying), uses open tabs to remember potential products (remembering), compares products in a consideration set (evaluation), and finally decides whether or not to buy a product (choice). Importantly, many of our participants engaged in iterative search processes, going back to “earlier” stages by reformulating queries, revisiting results pages in search engines or online shops, or entering new queries in newly opened tabs.

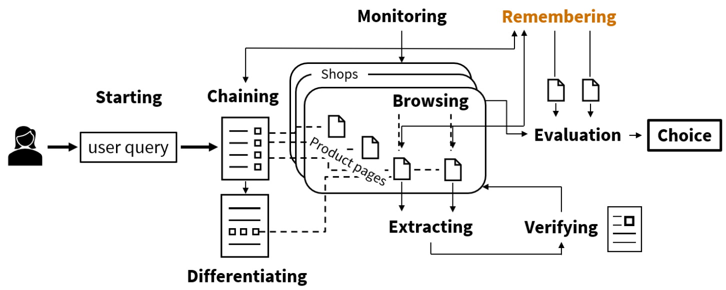

Figure 2. Information-seeking Stages During Product Search with the Newly Added Stage “Remembering”

LIMITATIONS

While this study offers valuable insights into users’ behavioral strategies during product search, several limitations should be noted. First, the sample size was relatively small (N=31) and limited to two product types. While this constrains generalizability, we believe that the setup was appropriate for qualitative exploration and yielded meaningful observations. Second, although the tasks simulated real-world shopping scenarios, participants knew no actual purchase was required, which may have affected their motivation and engagement—particularly in the absence of financial consequences. It is possible that these circumstances contributed to the *minimalist searching* behavior we observed. Third, all sessions were time-limited and conducted in a single sitting. While we recognize that real product searches often span multiple sessions (Li, Capra, & Zhang, 2020), we assume that the strategies identified are likely to occur in longer searches as well. Further studies are needed to confirm this. Finally, the study focused exclusively on desktop-based search. Behavior in mobile shopping—gaining in relevance (Statista, 2025)—may differ significantly, and certain strategies such as hopping between tabs and anchoring on results pages may be less feasible or take on new forms in mobile contexts, warranting dedicated investigation.

CONCLUSION

In this work, we investigated behavioral strategies of online shoppers during product search. We analyzed 48 individual product search sessions and systematically coded users’ behaviors across resources used, views seen, and actions taken, using an annotation scheme developed for this purpose. From these standardized descriptions of search sessions, nine behavioral strategies emerged. These strategies describe how people navigate throughout their search session, such as switching between browser tabs to compare products, following recommendations from product to product, and using result pages as an anchor for their search. We provide an overview of behavioral strategies for product search and present a new framework for online shopping, integrating our empirical observations into established information-seeking models.

Our findings also uncovered some differences in how people look for experience products (e.g., a jacket) and how they search for search products (e.g., a laptop). For example, *funneling* actions such as query (re)formulations and filtering to narrow down options were more often observed in jacket search sessions, while external (expert) information was consulted more frequently during laptop searches. However, our qualitative study setup does not lend itself to statistical analyses of these differences. Future work could quantitatively investigate these observations to confirm their statistical significance and effect.

By aligning platform features with the behavioral strategies we uncovered, e-commerce sites could better address the distinct needs of users. For instance, platforms could optimize layouts for frequently observed navigation patterns, enhance features that make product comparisons more seamless, and tailor the display of customer reviews or expert opinions based on product category. Taken together, these insights can foster more supportive and effective online shopping experiences.

GENERATIVE AI USE

We employed ChatGPT, Gemini, and Claude for the following purposes: improving the wording of paragraphs, helping with the creation of tables, and helping with the creation of data analysis scripts. We evaluated the output by carefully checking for factual correctness and logical consistency. The authors assume all responsibility for the content of this submission.

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