RETHINKING SEARCH INTENT: FROM TRADITIONAL SEARCH ENGINES TO LLM-POWERED INFORMATION RETRIEVAL

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Introduction

The digital information retrieval landscape has undergone major changes in recent years. Traditional search engines have transformed from simple hyperlink providers into platforms featuring rich snippets and direct answers (Lewandowski 2023, Oliveira 2023). Meanwhile, large language model-based (LLM-based) chatbots such as ChatGPT have emerged as popular information retrieval tools in addition to their conversational functions (Wang et al. 2024, Ouyang et al. 2023). As a result, LLM based chatbots now serve as alternatives to traditional search engines, challenging their dominant position in digital information access (Liu et al. 2024). In response, search engines have begun incorporating AI-powered results and introducing conversational interfaces, further blurring the lines between search engines and LLM-based chatbots (Reid 2024, Schwartz 2025).

These changes impact how people navigate these tools, shaping their expectations and goals, thereby challenging the applicability of traditional search intent frameworks. One of the most established frameworks for categorizing search intent is Broder's (2002) taxonomy, which classifies intent as informational, navigational, or transactional. This framework was developed in an era where search relied heavily on hyperlink-based navigation and remains one of the most widely used models today. Since then, the framework has seen only minor refinements (Rose & Levinson, 2004; Jansen et al., 2008), which do not sufficiently account for the evolution of search, specifically with LLM-based chatbots introducing new forms of intent that go beyond traditional categories (Karunaratne & Adesina 2024). Additionally, these traditional intent classifications remain fundamentally constrained by their system-centric orientation.

They are predominantly based on the analysis of explicit user queries, overlooking actual user engagement and the deeper cognitive motivations driving search behavior. As a result, they emphasize what users search for rather than why, overlooking underlying goals and the evolving nature of information-seeking (Marchionini 2006, Radlinski & Craswell 2017).

The aim of this paper is to propose a taxonomy that addresses the limitations of previous frameworks by adopting a more user-centered perspective. On the one hand, our proposed taxonomy reflects the changing search landscape by accounting for new interfaces, such as LLM-based chatbots and the increasing complexity of search platforms themselves. On the other hand, it goes beyond the analysis of explicit queries by accounting for users' underlying cognitive processes and evolving motivations throughout the search journey. To do so, we take the following steps: First, we assess Broder's (2002) framework by examining how well its search intent classifications capture contemporary search intent in modern search engines and LLM-based chatbots. Second, based on our assessment of Broder's (2002) framework, we identify the adjustments needed to develop a novel search intent framework. Third, we propose a novel, user-centered search intent framework that considers the entire search session, including immediate information needs, contextual triggers, outcome realization, and overarching personal goals. This multi-dimensional approach draws on motivational theories, such as the Schwartz Theory of Basic Values (2012), to better capture the underlying drivers of information-seeking behavior.

Study design

To address the research objectives outlined above, we conducted an online survey (N=82) that incorporated direct reflection on participants' recent search behaviors. Rather than relying on controlled lab-generated search sessions (Ageev 2011, Liu et al. 2019) or user logs (e.g., Mishne & de Rijke 2006, Silverstein 1999), our methodology asked participants to examine their actual search engine histories and LLM-based chatbot conversations, analyzing their last three sessions with each platform, resulting in a total of 246 sessions per platform. This approach allows us to reduce recall bias and provides more accurate insights into real-world search behaviors (Bolger et al. 2003, Tversky 1974, Porta et al. 2014, Tourangeau 2000).

Participants were guided through a structured reflection process based on Xie's (2002) model of interactive information retrieval. Specifically, we asked participants to describe their current search goal (the immediate information needed), their leading search goal (the situational context triggering the search), their long-term goal (the user's broader personal goal) and their interaction intention (their engagement with the search tool). To capture post-search behavior, we extended this framework by adding a dimension of outcome realization, which accounts for what participants did with the retrieved information.

In addition to search reflections, we collected demographic and digital skills data to contextualize future analyses.

Analysis approach and preliminary findings

To systematically assess search behaviors, we apply a structured analysis approach informed by both deductive and inductive coding methods (Braun & Clarke 2006). First,

we map both search engine sessions and LLM-based chatbot sessions onto Broder's (2002) search intent framework, categorizing them as informational, navigational, or transactional. This allows us to establish a baseline for how well the traditional taxonomy applies to contemporary search behaviors. Second, we identify shortcomings in Broder's framework by examining cases where user intent does not fit neatly into the existing categories. These discrepancies highlight areas where the framework requires adjustment and inform the development of preliminary categories that better capture modern search intent. In the third step, we map all search sessions onto these newly generated categories, which will be further refined as we progress toward developing a comprehensive, user-centered framework that consists of immediate search goal, contextual triggers, outcome realization, and overarching purpose.

Our preliminary findings suggest that traditional search intent taxonomies inadequately capture contemporary search behaviors. We identified three key observations. First, emergent patterns that do not fit existing categories, such as LLM-based chatbot interactions where users request specific tasks or actions outside of Broder's taxonomy. Second, the dissolution of boundaries between categories, with search sessions evolving from informational to navigational and transactional intents, thus fitting several categories at the same time, and LLM-based chatbot interactions blending informational and transactional intents. Third, a statistically uneven distribution of intent categories, with informational queries dominating across both search engines and LLM-based chatbots, while navigational queries being nearly absent in LLM-based chatbot interactions.

To address these observations, we propose an alternative classification of search intent that shifts the focus from what users search for to the intended use of the information. Rather than simply adjusting existing boundaries, this reclassification prioritizes the purpose behind the information need. We categorize search intent into three types: *knowledge-oriented* (general information, facts, or news), *solution-oriented* (advice, recommendations, or guidance to solve problems), and *resource-oriented* (specific websites, tools, services, or actions). This reclassification builds on our qualitative reflections by splitting the broad informational category into two distinct types of information needs and by collapsing the boundaries between navigational and transactional intents into a single resource-oriented category. These three categories represent the immediate search goal in our proposed search intent framework. While this reclassification addresses the **immediate search goal**, our qualitative dataset of search session reflections reveals that modern search behavior involves additional dimensions. To develop a more comprehensive framework, we plan to expand our taxonomy with additional dimensions, including **contextual triggers** (e.g., media exposure, social interactions, or internal curiosity), **outcome realization** (e.g., making decisions, solving problems, or satisfying curiosity), and **overarching purpose** linking searches to broader motivational structures. While contextual triggers and outcome realization can be derived from participants' self-reflections, overarching goals require a more systematic mapping. As the next step, we will draw on the Schwartz Theory of Basic Values (Schwartz 2012) to connect participants' self-reported search motivations to fundamental human values, allowing us to trace how immediate information needs align with broader personal goals. This multi-dimensional framework shifts the perspective from query-based taxonomies to a user-centered understanding of search behavior, unveiling the deeper motivations that drive information seeking.

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