Examining How Search Engine Users Understand the Production of Autocomplete Suggestions

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Abstract

Autocomplete is a popular search feature that automatically generates query suggestions for any keywords entered in the search bar. In this research, I examine regular end-users' folk theories of how general-purpose search engines produce such suggestions. Drawing on interviews with 20 search engine users, I found that users conceptualize Autocomplete as an automated agent that is influenced by three main factors: (1) searcher's personal search history and profile, (2) aggregate population-wide queries, and (3) commercial advertising. Users' assumption of these influences raises for them critical concerns about privacy, transparency, information insularity, targeted data manipulation, and the reproduction of societal biases in Autocomplete's outputs. My analysis also shows that users view *explanations* as a promising mechanism to enhance accountability in Autocomplete systems. I highlight the factors that shape users' mental models of Autocomplete and discuss how their algorithmic imaginaries stabilize platforms' revenue models.

Keywords

Google, autosuggest, autocompletion, autosuggestion, mental models, transparency, folk theories

Introduction

Let me begin with an illustration from my own use of web search platforms. One day, I opened the Google Search website to learn how to obtain visa for an upcoming conference travel. As soon as I typed in "how to," a list of ten autocomplete suggestions popped up, including "how to open xml file", "how to delete instagram account", "how to be more interesting," and "How to Train Your Dragon" (see Figure 1). Pausing (for once!) and reflecting on these suggestions raised several questions in my mind: do these suggestions say something about

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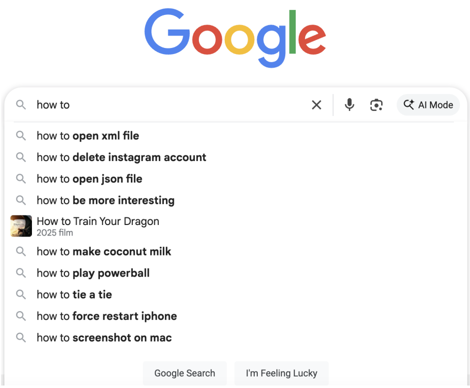

Figure 1. A screenshot of Google Search webpage showing ten autocomplete suggestions for the search terms "how to".

me and my interests and needs? Do they reflect what people in my neighborhood or people around the world are searching for? Am I witnessing ads disguised as products or beliefs that I *should* be attracted to? Do others see some or all of the same suggestions that I see with these search terms?

These questions speak to the process of *how* search engines produce autocomplete suggestions and what they reveal about this production process to their end-users. Notably, the Google Search webpage provides no answers to any of these questions. Its plain interface suggests neutrality and leaves no room for alternative suggestions. It appears that search platforms would prefer that their users just take these suggestions for granted and not question the underlying mechanisms that produce them.

However, prior research indicates that users may not just passively receive such suggestions, but actively reshape them through their practices (Dogruel et al. 2022). Indeed, Autocomplete[1] algorithms constantly process the queries they receive from users to rewrite their software (Graham 2022). Such recursive relationships between users and algorithms (Bucher 2019) raise the question of how users of search platforms relate to Autocomplete algorithms.

Previous studies on users' experiences of search platforms have examined how users formulate their search queries (Bilal and Kirby 2002), assess the relevance of search results (Saracevic 2007), and question the results provided (Juneja et al. 2024). However, these studies focus on search results and, as I will detail in the next section, few empirical studies have directly centered on the search Autocomplete feature. Markham (2024) theorizes that Autocomplete outputs

[1]Throughout this paper, I use 'Autocomplete' to refer to the technical feature that produces query suggestions on search platforms and 'autocomplete' to refer to each of the text suggestions that this feature outputs for any given search terms.

may not only shape how users complete their immediate search inquiries but also train them to think about search processes and search terms in specific ways over the long run. Yet, we have relatively little empirical data describing how end-users consume autocompletes or how they perceive platforms' processes for curating Autocomplete suggestions. Recognizing the ways that users interact with and make sense of this ubiquitous search feature is crucial to assess its functions and impacts. The current paper begins to fill this gap by examining users' folk theories of Autocomplete production and how users' understanding influences their impression and use of search platforms as a whole.

By attending to searchers' mental models[2] of how autocompletes are generated, I seek to clarify the aspects of Autocomplete operations that are already well understood and those that remain unclear. Based on my findings, I recommend the information that search platforms could provide to aid users' comprehension and use of this feature's outputs. Relatedly, I discuss the benefits, concerns, negotiations, and tradeoffs that permeate users' interactions with Autocomplete. I also analyze how users' consumer practices and information dependencies serve the 'capital accumulation cycle' (Fuchs 2011) of search platforms.

Background and Related Work

The Human-Machine Relation

Autocomplete has now become an expected feature of every mainstream online search—not just on web search platforms like Google and Bing, but also in search bars across social media, e-commerce, and other digital platforms. From the perspective of users, as soon as they begin typing a new search query, Autocomplete spontaneously produces a dropdown of query suggestions right below the search bar. These suggestions automatically update as each new character of the search query is typed in. Whenever a user selects an available suggestion, the search process completes, and the user is directed to a page of *search results* relevant to the selected suggestion.

Search autocompletes transform the information retrieval process into a persuasive and intimate human-machine dialogue (Markham 2024). For any given search terms, the suggested autocompletes subtly invite searchers to think in particular ways about those terms and direct them to certain types of information. Such micro-communication nudges influence how searchers engage in sensemaking and belief formation about the search terms. Influenced by the symbolic interactionist (Butler 1990; Goffman 1959) tradition, Markham (2016, 2024) argues that these cognitive effects last longer than the moment of individual searches and can, in the long run, even shape users' sense of identity.

[2]By *mental model* (Norman 1983), I refer here to a searcher's continuously evolving cognitive representation of how a search system works, especially how such a system curates and ranks autocomplete suggestions.

This relates to discussions about how micro-entities like Autocomplete can become intimate partners and serve with a form of “rhetorical energy” (Coleman 2021) through repeated cycles of everyday actions, back and forth responses, and negotiations between humans and agents. The use of Autocomplete also raises moral questions about responsibility attribution between humans and agents regarding what is said or done that are familiar within human-machine communications research (Guzman 2023).

The influence of machinic agency, as enacted by Autocomplete, may be especially strong for users of web search platforms like Google, as many of them use search services frequently, develop a close and trusting relationship with the platforms (Vaidhyanathan 2012), and may accept search outputs without much critical questioning. This paper examines how users’ trust in search platforms influences their understanding and consideration of Autocomplete outputs.

Crucially, prior research has shown that autocompletes can be biased, capricious, and subject to manipulation (Markham 2024; Miller and Record 2017), yet users’ trust in search platforms may leave them vulnerable to such information distortions. For example, Epstein et al. (2024) conducted a series of experiments which showed that negative bias in search suggestions regarding political candidates can impact people’s voting preferences without them perceiving any search bias. This vulnerability is especially significant to scrutinize because search engines like Google are, globally, some of the most powerful curators of information.

Scholarly Critiques of Autocomplete Production

Search platforms provide little information regarding *how* they generate autocomplete suggestions. Prior research on autocompletes has also paid relatively little attention to this generation process, focusing instead on evaluating the content of autocompletes and examining the biases or stereotypes they embody (Baker and Potts 2013; Ha et al. 2025; Leidinger and Rogers 2023; Olteanu et al. 2020). However, a few journalists and media scholars have made informed guesses about these procedures (Miller and Record 2017; Graham 2022).

These scholars conclude that Autocomplete implementations deploy sophisticated neural networks[3] that represent search terms as vectors, i.e., mathematical representations of data, in a higher dimensional space, and retrieve similar vectors in their index, as measured by the “distance” between vectors, to produce relevant suggestions (Hiemstra 2009). Experts surmise that the features that constitute Autocomplete models include the number of queries and click-throughs for a search term, the searcher’s location and other personal use data, search language, search trends, and previously selected suggestions (Miller and Record 2017;

[3]Neutral networks are machine learning models that use interconnected nodes or “neurons” organized in layers, which send signals to one another. These models process data, recognize hidden patterns and correlations, and continuously improve their learning over time.

Sullivan 2022). I examine in this article how regular users' understandings of Autocomplete production aligns with and differs from this expert understanding.

Enacting Autocomplete implementations involves a range of ad-hoc decisions, and search platforms frequently tweak their models to omit outputs that lead to public outrage, negative media coverage, or defamation court cases. Yet, such responses seem to merely hide, rather than address, Autocomplete's underlying problems of bias and discrimination (Graham 2022). Autocomplete's reliance on collective search behaviors also raises normative questions about this technology's epistemic responsibilities. As Miller and Record (2017) point out, "the mere fact that something is popular does not guarantee its correctness or usefulness." Since Autocomplete partially relies on click-through rates, popular autocompletes may become even more popular in a feedback loop, potentially amplifying sensational suggestions for any search term. This is especially concerning given that autocompletes are generated automatically and usually without any human supervision. I examine in this paper how regular end-users perceive and respond to these challenges.

Placing Autocomplete implementations in the context of search engines' business models raises several ethical questions (Graham 2023). Scholars have especially raised concerns that these business models are based on consumer profiling, i.e., users receive search services for free, but their data is translated into user profiles and sold to advertising clients (Van Couvering 2008). These intrusive practices of user profiling have been discussed in terms of "surveillance capitalism" (Zuboff 2019). Mager (2012) argues that "search engines and their commercial orientation are enacted in a socio-political context characterized by a techno-euphoric climate of innovation, a neoliberal policy of privatization and legal frameworks that fail to grasp global search technology." Mager (2012) further contends that users, in particular, solidify search platforms and their economic logic by complying with platforms' scheme of exploitation to satisfy their desire to keep consuming (Bauman 2013). I complement this strand of scholarly critiques by describing regular users' orientations toward consumer profiling and how they trade-off privacy concerns with search efficiency gains in the context of using search autocompletes.

Users' Understanding of Autocomplete Production

Despite the ubiquitous availability of Autocomplete in web search platforms, it remains unclear what makes users notice them and how they impact users' search behaviors. Since the set of autocomplete suggestions changes with the entry of every new character in the search bar, many suggestions may not grab the searcher's attention. Therefore, I first examine the factors that make it more likely that end-users notice autocompletes. I also inquire how users perceive autocompletes as shaping their search behaviors.

Relatedly, we do not yet know how regular end-users understand the production of autocompletes. The use of sophisticated machine learning models, the fleeting nature of Autocomplete utterances, and the common lack of feedback about the underlying production process make it more likely that end-users develop inaccurate mental models of how autocompletes are generated. This matters because even when users' mental models of any tool are not accurate, stable, or detailed, they guide users' expectations of that tool and influence how well they use it (Norman 2013). Therefore, as I elaborate below, this article primarily focuses on understanding users' mental models of autocomplete production.

Prior research has examined users' mental models of different aspects of online search. For example, Zhang (2008) analyzed students' mental models of search engines' working mechanisms and found that these models are influenced by personal observation, communication with others, and class instruction. The current article similarly examines how users come to develop the mental models they have about Autocomplete production. Thomas et al. (2019) investigated users' understanding of how search engines select and rank their search results to inform the provision of explanations in search systems. Muramatsu and Pratt (2001) evaluated searchers' knowledge of query transformation employed by search engines such as stop word removals and boolean operators. While this prior literature has largely focused on search results, I focus on understanding users' mental models of how Autocomplete suggestions are produced.

In addition to examining what regular users believe are the influencing factors driving Autocomplete suggestions, I also study how users critically evaluate platforms' presumed reliance on these influences. For example, if a participant believes that their prior search queries influence their future autocompletes, this research will seek to unravel that participant's privacy and security concerns—if any—about platforms' use of their search data. Engaging in this second-order analysis produces a more comprehensive picture of how users perceive the validity of Autocomplete suggestions, assess their utility and harms, and protect themselves against suspected information biases.

In assessing users' mental models of Autocomplete, I draw from prior literature that employs the concept of "folk theories" to study how people understand algorithmic processes on digital platforms. DeVito et al. (2017) define folk theories as "intuitive, informal theories that individuals develop to explain the outcomes, effects, or consequences of technological systems, which guide reactions to and behavior towards said systems" [p. 3165]. Folk theories are rooted in users' experiences of system interaction, accommodate uncertainty and internal contradictions in users' understanding of complex systems, and are naturally malleable over time (DeVito 2021; Ytre-Arne and Moe 2021). Many studies within the fields of Human-Computer Interaction (HCI) and media and communication research have effectively applied folk theory frameworks to examine users' perceptions of algorithms, largely focusing on algorithmically produced news feeds in social media platforms (DeVito 2021; Eslami et al. 2016; Karizat et al. 2021; Ytre-Arne and Moe 2021). I add to this research by analyzing users' folk theories of algorithms in the specific context of the search Autocomplete feature.

Previous research has highlighted users' demands for search platforms to be more transparent about how search results are produced, especially regarding moderation of inappropriate results and whether higher positions in the search results are for sale (Juneja et al. 2024; Thomas et al. 2019). Autocomplete outputs differ from search results in that they are responsive in real-time, limited in number, and have unknown origin. Thus, they may present a somewhat different set of transparency concerns. Therefore, I assess users' transparency needs regarding how Autocomplete functions.

Methods

This study aimed to examine regular users' understandings of how search engines generate autocomplete suggestions. Therefore, I set out to interview a diverse group of people to explore their mental models of the Autocomplete feature and how these views shape their perceptions and concerns about search platforms.

Prior to data collection, the study received ethics approval from the relevant institutional ethics board. I recruited interested individuals to submit their responses to a pre-screening survey through digital flyers and word-of-mouth. Using these modes allowed me to access participants from broad geographical areas and diverse populations. The recruitment message I used during this process is included in Appendix. This message briefly specified the goals and expected contributions of the study so as to encourage interested participants to complete the prescreening survey linked in the message. This survey was open between Feb 19 – July 29, 2025, and received 161 responses. I was assisted in this recruitment effort by Volunteer Science,[4] an online platform that connects researchers to subject pools for conducting behavioral research. I was recommended to use Volunteer Science by a faculty colleague who frequently uses their services for study recruitments and had earlier served on their team. I received sufficient responses through Volunteer Science and did not need to consider any alternative services to help with my recruitment.

Prior research suggests that experience with search features may be an important factor in shaping users' mental models (Holman 2011). Therefore, in the pre-screening survey, I asked respondents how frequently they use search engines, whether they have noticed search autocompletes, and what they think determines the content of Autocomplete suggestions. These questions guided selection of participants with diverse experiences and perceptions of Autocomplete feature in an effort to elicit a range of folk theories and concerns regarding autocomplete production during the interviews.

The survey also included questions about proficiency in information fields and demographic details. Similar to prior research in this space (Juneja et al. 2024; Thomas et al. 2019), I was primarily interested in the views of non-technical

[4]https://volunteerscience.com/about/

individuals since most users of general-purpose search platforms do not have special technical knowledge and skills. Understanding these users' assumptions, expectations and attitudes is vital to inform the design of search systems that serve everyone, not just IT experts, who are more likely to have a sophisticated understanding of information retrieval and machine learning concepts. Therefore, I excluded respondents who had developed or supported IT systems, worked in a library, or had an educational degree in Computer Science, Information Technology (IT), Library and Information Science (LIS), or a closely related field.

Additionally, I filtered out respondents who failed an attention check question. This question, borrowed from Rosenzweig et al. (2025), asked participants to "Please select 'Strongly agree' to show you are paying attention to this survey" with responses on a 5-point Likert-type scale. Since this question had only one (out of five) correct response, survey takers had a low likelihood of correctly answering this question without paying attention to the survey. From the remaining pool, I selected 20 individuals for follow-up interviews, ensuring the sample was both demographically diverse and represented a range of perspectives on Autocomplete. Table 1 (in Appendix) presents the demographic details of interview participants.

All interviews were conducted in-person or via Zoom. During these interviews, I asked participants what they thought influenced the autocomplete suggestions they saw in their daily use. For each influencing factor that participants mentioned, I questioned how they perceived the benefits and risks of Autocomplete relying on that factor. Some of my participants had not particularly considered critical aspects of Autocomplete before the interview and had taken this feature for granted. These participants developed a more reflexive stance on Autocomplete's ethical and operational issues during the course of the interview despite my refraining from asking any leading questions.

Given the dominance of Google in the search engine market, my interviewees typically, although not exclusively, focused their discussions on Google Search and its autocomplete offerings. Upon completion of the interview, each participant received a $20 Amazon gift card as compensation for their time.

I recorded each interview after obtaining participants' consent and subsequently transcribed it for analysis. Interview transcripts were cleaned and de-identified, and then uploaded to Dedoose, a qualitative analysis software, for thematic coding using inductive analysis (Braun and Clarke 2006). I used Dedoose (over other alternatives like NVivo and MaxQDA) because my school provides free access to it, and I was already familiar with using it through prior projects.

I began analysis by reading the transcripts multiple times. Following this, I engaged in line-by-line coding, such that initial codes stayed close to the data. Next, through an iterative coding process, I refined and consolidated my initial codes into a set of parent codes and corresponding child codes. For instance, the parent code "Assuming that ads influence Autocomplete" included the child codes "Reasons for this assumption", "Attitudes toward ads", and "Lack of transparency about ads." I examined how these codes relate to one another and developed thematic connections between them. Throughout the analysis, I wrote research memos to document my emerging insights. Finally, I developed thick descriptions of codes as key themes that I present as my findings below.

Findings

Noticing Autocompletes and Their Influence

Participants observed that they often notice autocompletes as they are in the process of typing out their search queries. This noticing becomes especially likely when their desired search queries are longer in length, not yet fully developed in their minds, or when search engines are used on mobile devices instead of desktop devices. For example, P17 said:

> *"If I'm using mobile, generally, I'm finding that I'm using them more. It's a faster, more expedited experience. It's generally getting me to that result faster than me having to type it with my thumb."* – P17

More broadly, participants noted that they more heavily rely on autocompletes in situations when they are not at their full capacity to type out the full query, e.g., when they are distracted or walking. Indeed, in such cases, they select autocompletes even when it does not precisely capture their desired search query. Thus, participants navigated a **tradeoff between control and efficiency** in specifying their search queries when interacting with the search autocomplete feature.

Many interviewees described the influence of autocompletes as **"subtle" or "unconscious."** For example, P2 said that while typing out search queries, autocompletes appear in his "not quite peripheral vision," and thus they are attention grabbing. Some felt that the position of each autocomplete, i.e., its rank order in the list of suggestions, influences how likely it is to draw their eyes. Crucially, some participants noted instances when autocompletes subtly pushed them in certain search directions that they were not already thinking about. P7 described:

> *"Every once in a while, something that will pop up, and it's not what I intended to search originally. And I'll be like, oh, is that happening? Or oh, I didn't realize that. And autocompletes will make me think like, oh, is there something else that I'm missing here? And then I'll end up searching what it suggested for me to search, you know."* – P7

Some participants tended to anthropomorphize Autocomplete by characterizing it as a persistent **conversation partner** who is in a fast-paced dialogue with them, who remembers their recent topics of exploration, and who is responsive to their input. For example, P11 described:

> *"After I watch a movie, I will put it into Google and see what the autocomplete says, because I'm wondering if there was ever any drama*

> *on set, or if there was, like, problem with the box office. So if you just type in the name of the movie into Google, sometimes you get interesting autocompletes. So yeah, it's like a friend that says, 'Have you heard?"'* – P11

Noticing these autocompletes in their daily use naturally generated **curiosity** among many participants regarding *how* search engines generate them. P13 characterized Autocomplete as a "really powerful technology" and remarked that she would be fascinated to know how it works. P2 wondered about the extent to which the mechanisms of Autocomplete are a trade secret and therefore cannot be divulged by search engines. Such curiosity was particularly piqued when participants observed surprising or unexpected autocompletes. For instance, P1 noted:

> *"If an autocomplete suggestion they offered to me was extremely accurate, I don't really think I need to know what their model is, because I can make some guesses as to why they provided that to me. If it was pretty far from what I was looking for, then I would be really curious as to why, like, what are the particular reasons why they showed me this search suggestion."* – P1

Seeing Autocomplete as a Learning Agent

Participants conceived of Autocomplete as an **automated agent** that attempts to understand their search intention. P14 especially appreciated that as she types in more and more characters in the search bar, the autocompletes update to become progressively closer to her desired search query. Most interviewees assumed that sophisticated datasets and algorithms or complex statistical models underlay the functioning of the Autocomplete feature. For instance, P1 said:

> *"I suspect that it's probably a model that includes multiple variables. And these variables are probably weighted based on current information or historical information."* – P1

Participants noted a distinct lack of information that search platforms provide regarding how they generate autocompletes. They perceived this **lack of transparency** by the platforms as strategic and deliberate, e.g., according to P3, "search engines just want to fly under the radar. They don't really want to get us all thinking about this." However, many participants desired platforms to create support pages that provide clear descriptions of how various factors are integrated to curate autocompletes. Some participants wanted to see this transparency at a more granular level. For example, P7 said:

> *"Ideally, for everything that shows up in autocompletes, you should see just a quick phrase for why it's showing up there."* – P7

While most participants could not conceptualize exactly how Autocomplete integrates different information sources, they believed that this feature relies on a variety of factors. Every participant was able to list several such influencing factors. Participants' mental models of such influences were often derived from their observations of variations in autocompletes while searching on different devices (e.g., desktop, mobile), various browser settings (e.g., private or incognito mode; deleting cookies or browser history), and in distinct locations. For example, P11 deduced that location is an influencing factor when observing Autocomplete outputs away from her home city:

> *"I'm from Poland, and so whenever I go visit my family in Poland, and I'm looking something up even in English, it starts to auto-complete things in Polish...And then also, if I'm in a different state, it would show 'grocery store Florida' instead of 'grocery store NYC'."* – P11

The following factors were the most prominently described by participants as the likely influences on Autocomplete: (1) their **own data** on the search platforms, including their prior search activities and search location; (2) **other users' searches**; and (3) platforms' **commercial interests**. I will delve into participants' perceptions of each of these three factors below and discuss how they raise concerns about privacy, transparency, information integrity, and reproduction of societal biases in Autocomplete outputs. Besides these key factors, several participants also suspected that Autocomplete curation incorporates a wide range of other factors that they may not have considered. P2 pointed out:

> *"I think, any complexity that we can think about in terms of how the [Google Autocomplete] algorithm is structured has been taken into account by Google engineers who have thought about this much more than we have."* – P2

Assuming Autocomplete's Reliance on User Data Raises Concerns About Privacy and Lack of Information Diversity

Almost all participants expected that their **prior search queries** influence the future selection of autocompletes they see in their searches. While some participants appreciated the efficiency gains that this factor presumably delivers by presenting catered search results, others expressed concerns about being locked into an **information "echo chamber."** For example, P15 worried about Autocomplete profiling his interests too narrowly and suggesting less diverse cues when switching from one search topic to the next. Similarly, P20 complained about Autocomplete suggesting content that he has already consumed:

> *"So if I hit like Y for YouTube, the first or the second recommendation is usually, like, whatever YouTube video that I have already watched. And if I accidentally click on it, it just repeats in like a feedback loop. I don't need to rewatch it that many times."* – P20

Besides prior search queries, participants identified other types of **private internet use data** that they believed could be shaping autocompletes. For example, given that Google Workspace has a range of associated services, such as Gmail and Google Maps, many participants expected that data from such services are also used to predict autocompletes for logged-in users while using Google Search. Additionally, twelve interviewees assumed that their **location** is used to personalize their autocompletes. P19 observed different autocompletes when using his internet browser in incognito (i.e., private) mode; this observation led him to believe that autocompletes rely on **browser cache and cookies**.

Building upon their understanding that search platforms draw from a variety of private user data, many participants further surmised that search platforms build a "user genome" (P9) or **demographic profile** for each user (e.g., Asian, female) based on such data and then customize autocompletes to fit that profile. Some participants were repelled by the idea of Autocomplete profiling them based on their demographic characteristics, such as their age or gender, as they considered themselves not fitting the stereotypes associated with such markers. For example, P17 described:

> *"I don't like the personalization just because I find it fits me into a user story or something like that, that just puts me down a path of getting in my way when I'm browsing rather than aiding my browsing."* – P17

I asked participants their perspectives on Autocomplete's supposed use of their private user data. Surprisingly, most participants expressed little concern about Autocomplete's potential **privacy intrusions**. For example, P7 felt that he is not a public figure, and therefore, no one would care about his personal information on search platforms. P2 commented that while this lack of privacy makes him uncomfortable, it is "the price of having free services that are as powerful and life changing as [web] search is." P1 and P10 expressed a sense of futility regarding preserving their data privacy online. They remarked that digital platforms already have access to their data, so they might as well use this data to improve their search offerings. For example, P10 shared:

> *"My personal information is being used by so many platforms in so many ways that I cannot control and is not useful to me. This one is at least useful to me, so this one I don't mind."* – P10

However, a few participants expressed unease over the loss of user privacy that accompanies the use of Autocomplete feature. These participants were concerned about the sheer volume and diversity of user information that search platforms possess, including not just their demographic characteristics and likes or dislikes, but also their core values, fears, and beliefs. For instance, P19 noted:

> *"It knows so much about you. It knows what you've searched for in the past. It knows what websites you've been to. It knows where you've shopped. It knows where you've been."* – P19

Additionally, these participants raised questions over exactly who gets access to their search data, how long they store it, and how they use it. They also desired platforms to be **more transparent** regarding how they are collecting user data and the security measures they are employing to protect that data.

Assuming Autocomplete's Incorporation of Other Users' Searches Raises Concerns About Reproduction of Subjective Biases

15 (out of 20) participants assumed that Autocomplete incorporates population-wide search queries to shape its suggestions. For instance, P11 estimated that given any query letters typed-in in the search bar, autocompletes are shaped by "what **people in the area** have googled the most based off of the characters" in that query. P8 had a similar mental model, although she assumed that Autocomplete is influenced by what "**people around the world**" are looking for, not just searchers in her neighborhood. P13 envisioned search platforms maintaining a database that tracks which suggestions users select among the given autocomplete prompts and **prioritizing selected prompts** in the future. Similarly, P2 assumed a "positive feedback loop" that renders selected autocompletes more likely to appear before future searchers.

Participants based these beliefs on their regular observations of autocomplete suggestions. For instance, P10 deduced that when she types in the letters 'gr', the suggested autocompletes include 'grocery store near me' because it "is a very common thing to search" for most people. Interestingly, for three participants, this mental model was reinforced by watching pop culture narratives (e.g., Wired magazine's Autocomplete interviews[5]) which presume that autocompletes reflect most-searched queries.

Many participants appreciated Autocomplete's assumed use of others' searches, as they believed this apprises them of **relevant trends** and news about their search keywords. For instance, P17 noted selecting autocompletes that made him think, "Oh, other people are searching for this. This may be something I need to know about!" P15 drew an analogy with the free-market system, appreciating that the reliance on population-wide queries lets "the market" decide what information is most salient to suggest as autocomplete prompts. This shows how reliance on the metaphor of the "Marketplace of Ideas" (Morrow and Wihbey 2023) may promote users' preferences for neoliberal approaches to determining search outputs.

Six interviewees saw Autocomplete as a **lens to understand society**. For instance, P13 argued that autocompletes can bring visibility to the symptoms of emerging diseases and therefore support public sensemaking around vital biological trends. P7 admitted his interest in simply seeing "what's going on in the heads of other people" and viewed Autocomplete as a tool to satisfy his curiosity about what other people are searching. P11 similarly noted:

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[5] https://www.youtube.com/playlist?list=PLibNZv5Zd0dwjZFCTVZ8QdKq194CkwXjo

> *"I think these autocompletes are like a very easy and very quick way to get a poll of the general population that uses Google in terms of different topics. It's very interesting! Instead of going through the process of doing meticulous research about people's opinions around the world, you're able to just type in a few words, and it's going to show you what people are thinking."* – P11

However, participants also raised **concerns about** Autocomplete's potential reliance on population-wide searches. For instance, P1 worried that since many people today are searching for **misinformation**, such as "holocaust is fake", Autocomplete models may interpret these as desirable prompts and perpetuate information distortions. Similarly, P13 expressed concerns about Autocomplete reinforcing **identity-based biases** and stereotypes:

> *"If the search suggestion is coming up because a lot of other people are searching for it, society isn't nice, right? It's full of conflicts and inequalities, and built-in biases and lots of discrimination. And I guess, unfortunately, that is going to show up in our search engines, too."* – P13

Given the potential for such inappropriate autocompletes, many participants emphasized the importance of consuming Autocomplete prompts with a critical eye. However, they also worried that many search engine users, especially younger people and digital novices, assume that search platforms always provide factual information, and such users would not be able to distinguish between **truth and subjective opinions**. P19 pointed out:

> *"A lot of people are not deep critical thinkers, right? They have a lot of other things to do that eat up their time and efforts. And a search result is taken as gospel."* – P19

A few participants also raised concerns about Autocomplete being vulnerable to **targeted information manipulation**. P15 worried about market actors exploiting bots posing as search engine users and artificially simulating popular interest in specific queries to influence Autocomplete. Similarly, P16 noted:

> *"I don't know what would happen if a whole group of people decides — oh, we're going to type this exact same thing just to get a biased result. Whether it's a certain political group or a group that's against something or for something. That could be a problem!"* – P16

Assuming Autocomplete's Incorporation of Platforms' Commercial Interests Raises Transparency and Information Integrity Concerns

14 participants assumed that Autocomplete prioritizes suggestions that lead searchers to commercial **entities that advertise** on the search platform. These

participants reasoned that search platforms like Google and Bing are private, for-profit corporations whose primary goal is not to provide fair and accurate information, but to earn profits, usually via advertising dollars. Additionally, they argued, many companies and organizations are deeply invested in promoting their presence online, making it likely that they would buy ads to prioritize their appearance among search autocompletes. For example, P16 said:

> "*I assume companies are probably paying Google to kind of be their number one search autocomplete kind of thing. And I guess, for Google, it's a way for it to make money.*" – P16

When these participants suspected that autocomplete suggestions were actually *disguised* advertisements, they felt "manipulated" (P2) and their **trust** in the integrity of the search outputs **declined**. P13 feared that such advertising centralizes information for any product inquiries around large corporate actors and "marginalizes the small local shops." Some participants worried that autocompletes show not only commercial products, but also political and social views based on who pays search companies for ads, rather than on what's most relevant to the search query. Similarly, P6 stressed:

> "*I don't want people to be able to pay to influence in a way, because my understanding of Google is, it was designed so that I can go to find information, factual information that's not biased or skewed.*" – P6

Other participants were more accommodating of search engines serving their commercial interests as long as they provide autocompletes that are relevant to their search queries and do not detract from their search intentions. These participants did not see the influence of advertising as an ethical failure; instead, they were primarily concerned with the "material helpfulness" (P9) of autocomplete prompts. P2 emphasized the need for search companies maintaining the usability of autocompletes as follows:

> *"I think there's a balance between Google sort of making short term profit off of advertising, and these, like, direct payments from vendors, as opposed to actually giving users good results. And were it to veer too much in the direction of saying, pay me, and I will put your business higher up on the [autocompletes] list, I think that would be do more harm than good in the long term, right? You want to be long term greedy, not short term greedy."* – P2

Participants noted that while Google search results label advertisements with a 'Sponsored' tag, no such label appears within its autocomplete suggestions. This **lack of transparency** makes it difficult to ascertain when they are being served advertisements instead of "organically popular" (P9) autocomplete prompts. Many interviewees felt that search companies have an obligation to declare when autocompletes are ads although they admitted that they are likely to pay lesser attention to sponsored suggestions. P20 said:

> *"I certainly think that it should be disclosed if an autocomplete is sponsored. If it's not, then that's a little bit nefarious. It's like attempting to control the flow of information without proper disclosure."* – P20

Discussion

This study sought to first understand how regular users notice search autocompletes and perceive their influence on search actions. I found that users view autocompletes as an instrumental shortcut to arrive at their desired search results, often selecting them to save time and the micro-labor involved in typing out their queries themselves. Such interactions frequently compromise on inputting exact search intentions to achieve greater efficiency. This trade-off has consequences not only for what users search but also what they ultimately learn and believe. Crucially, an over-reliance on Autocomplete's algorithmic nudges may leave users more vulnerable to manipulation and bias (Baker and Potts 2013) embedded in search infrastructures.

Many of this study's participants recognized that Autocomplete's nudges influence them in a subtle, almost unconscious, manner. Some were inclined to anthropomorphize Autocomplete and viewed it as an eager and helpful conversation partner. A few even admitted to autocompletes entirely reshaping their search directions. These insights add empirical support to Markham's conceptions of how micro-entities like Autocomplete can become a relational partner and induce changes in users' inquiry formation processes (Markham 2024, 2021). Users' personal relationship with Autocomplete, as documented in this paper, is especially striking given the relatively mundane affordances of Autocomplete compared to increasingly popular generative AI applications, like ChatGPT, that are even easier to anthropomorphize.

Given this personal and regular relationship, users often wondered how Autocomplete works, as per my analysis. However, search websites reveal little information about autocomplete production. Additionally, the entry of each new character in the search bar updates Autocomplete's suggestions quickly and dynamically—this makes it more difficult for users to critically examine its outputs as compared to the outputs of search results. Still, my findings show that regular users, owing to their daily and extensive use of web search platforms, often across different devices, web browsers, topical inquiries, and locations, encounter a range of data and comparison points about search autocompletes. Over time, this knowledge helps users form detailed and informed, yet still incomplete and imperfect, folk theories of how search platforms likely produce autocompletes. Specifically, all my participants understood Autocomplete as an automated agent and could list multiple factors that may be influencing its outputs. My data further show that users build upon these mental models to form implicit assumptions about Autocomplete's benefits and risks, which in turn also influence how they perceive and consume its suggestions.

Markham (2024) writes that the power of micro-helpers like Autocomplete lies in the deliberate invisibility of their production process because it makes their outputs appear neutral and staves off questions about whether alternative suggestions could be delivered. However, my findings about regular users' mental models suggest a deep dissatisfaction with platforms' lack of transparency about autocomplete production. Moreover, they characterize this opaqueness as intentional and recognize how it serves platforms' interests under the guise of providing utility and function. Indeed, I found that a lack of transparency is a key concern for users in several aspects of how Autocomplete systems work: which data they collect to produce suggestions; how they store, protect, and use this data; how personalization and population-wide interests are incorporated in shaping Autocomplete outputs; and whether advertisers are prioritized.

Prior research has proposed the provision of search explanations as a salient strategy to enhance transparency and accountability in search results (Thomas et al. 2019; Singh and Anand 2019). My data add evidence to the user needs for such explanations in search *suggestions* as well: my participants desired to see metadata for each autocomplete that shows why platforms consider it relevant and whether it is sponsored. There is already some precedence for providing such metadata in similar contexts, e.g., Google Search offers an "About this result" panel[6] for each of its search results, which describes how that result relates to the corresponding search query and search settings. Similar to this, tagging each autocomplete with the key factor(s) shaping its inclusion (e.g., "previously searched", "near your location", "sponsored") would provide users additional context to judge its utility. I recommend that system designers experiment with the design space of information labeling (Morrow et al. 2020) as a crucial remedy to reduce transparency gaps regarding autocomplete suggestions and increase user trust.

Scholars have long criticized search engines' business models that are based on consumer profiling (Van Couvering 2008; Zuboff 2019). I found that regular users today show an awareness, at least at an abstract level—or what DeVito (2021) calls folk theorization at a functional level—that their data is being used to shape their autocompletes. They presume that Autocomplete profiles them, yet they remain uncertain about exactly which types of data (e.g., prior search queries, demographic information) search systems use to build their user profile. Most of my participants expressed a sense of resignation regarding their loss of privacy on search platforms. This is concerning because it highlights that the 'service-for-profile' business model (Elmer 2003) has become so entrenched across prominent digital services that privacy loss is now just assumed and accepted by the general public. These insights also align with prior work on "digital resignation" as a rational emotional response by consumers in undesirable situations that they cannot combat (Draper and Turow 2019).

[6] https://support.google.com/websearch/answer/10563935?hl=en

On the other hand, the idea of consumer profiling raised utility concerns for many participants: they worried about being locked in an information echo chamber and not being shown relevant or diverse suggestions. This is in line with social media users' apprehensions about personalized news feed algorithms isolating them in a unique information universe (Pariser 2011; Plettenberg et al. 2020). More broadly, these insights should inspire public policy interventions around limiting data gathering and regulating targeting practices of search platforms.

Besides their own private search data, participants usually assumed that Autocomplete leverages other users' aggregated search data. This folk theory aligns with Eslami et al. (2016)'s Global Popularity Theory of Facebook news feeds, in which the algorithm is believed to privilege popular content. Many participants appreciated this assumed reliance on population-wide searches as they felt it provided them a reflection of societal beliefs and informed them about recent trends. However, others raised concerns about how such processes raised the likelihood of targeted information manipulations, stereotypes, and misinformation appearing in autocomplete outputs. While participants usually deemed themselves capable of distinguishing objective truth from subjective opinions when consuming autocompletes, they worried about vulnerable others, especially children, who may be negatively affected by such information distortions. This insight helps advance third-person effects research in digital media (Riedl et al. 2021; Jhaver and Zhang 2023; Ytre-Arne and Moe 2021) by showing how perceived effects of search offerings on others may play an important role in shaping users' perceptions of search platforms' responsibilities.

Graham (2022) asserts that the extent to which user queries influence autocompletes is often over-estimated, and this misunderstanding is perpetuated by the media and academics. Lack of information released by search engines about Autocomplete production further reinforces this over-estimation. My data aligns with this: as mentioned above, I found a widespread belief among the study participants that autocompletes derive from their own prior searches and population-wide searches. Participants often blamed inappropriate suggestions on societal biases and queries made by other users. However, evidence suggests that many inappropriate autocompletes stem from search engines' application of machine learning rather than actual user queries (Graham 2022). This matters because such a misunderstanding allows search platforms to avoid taking the full ethical responsibility of reifying problematic outputs–even while maintaining users' trust and benefiting their revenue models. Greater transparency regarding autocomplete production would assign liability for inappropriate suggestions more accurately to how they are produced within the system (Graham 2022).

In my review of search engine policies, I could not find any clear evidence for whether websites like Google Search and Bing Search use signals from their advertising platforms to inform Autocomplete. However, Google Ads offers a "Map suggest ads" feature that explicitly allows advertisers to appear as autocomplete suggestions on the Google Maps mobile app (Google Ads

2025). Many of my interview participants assumed that advertising influences Autocomplete suggestions and, more crucially, they were usually willing to put up with some level of advertising as long as it did not detract from the material helpfulness of autocompletes. This suggests that users are not just passively exploited by search engines but are rather seduced into an alliance with search platforms to achieve their information goals. These social practices align with Mager (2012)'s conception of how users—both consciously and unconsciously—stabilize the capitalist 'spirit' of search engines with their own search and consumer actions. Thus, we must go beyond examining the societal impacts of Autocomplete toward understanding the socio-political cultures that co-construct its algorithmic ideologies (Seaver 2017; Beer 2019).

Limitations

The recruiting channels I used for this study influenced the composition of my participant sample. This sample is especially better educated than the general population, and thus it may have had more training in conducting critical analysis and considering ethical issues. That said, I did not seek to build a representative sample for this study, as my goal was to attain an in-depth understanding of critical issues with Autocomplete production rather than broad generalizability. However, more research is needed to determine the transferability of the presented findings. For example, survey studies with nationally representative samples that examine the prevalence of various folk theories identified here or that evaluate the extent to which users remain concerned about privacy, transparency, information diversity, etc. regarding autocompletes would be valuable.

Conclusion

This article aimed to understand what makes search engine users notice Autocomplete suggestions. My interview data provide early insights, highlighting the subtle and seemingly unconscious nature of their influence and identifying a control vs. efficiency tradeoff that users engage in when using autocompletes. Further studies using experience sampling methods and extended search logs would be valuable to more fully capture how and when users pay attention to and interact with autocompletes.

Most crucially, this research sought to explain how regular end-users conceptualize the machinery that produces autocompletes. My findings offer detailed descriptions of users' folk theories of autocomplete production. These folk theories clarify aspects of Autocomplete that are already well-understood and those that remain unclear, and can guide future efforts toward enhancing algorithmic literacy among search users. I had aimed to compare experts' and lay-users' understanding of Autocomplete. Toward this goal, my data show that most users' folk theories are less mechanistically complex (DeVito 2021) than experts' beliefs, yet they recognize many of the key influences that, scholars believe, shape autocompletes.

I conducted a second-order analysis to answer how users' mental models of autocomplete production impact their perceptions of search platforms. Findings show that users appreciate the potential problems of privacy loss, lack of transparency, and perpetuation of societal biases associated with Autocomplete outputs. However, these concerns are usually overridden in users' quest to quickly and efficiently find information. Thus, we need a collective effort by designers, researchers, journalists, activists, lawmakers, and the public at large to reconsider search technologies and instill greater transparency and accountability in Autocomplete tools.

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Appendices

Recruitment Message

I am a researcher from <Anonymyzed> University conducting a research study to understand users' mental models and preferences of how Google Search selects, ranks, and moderates its search autocomplete suggestions. Would you like to participate in an interview study to discuss your use of and preferences for Google Search? Your input will help inform the content curation and moderation efforts of autocomplete tools.

You can express your interest in participating in our study by completing this survey. Based on your responses, we will contact you for an interview if you are a suitable candidate. Participants selected for the interview will receive a $20 Amazon gift card after completing the interview. Please note that there is no reward for completing this survey alone.

Contact Info of Principal Investigator (PI):
Name – <Anonymyzed for review>
Email – <Anonymyzed for review>

Participant Information

Table 1 shows the demographic details of interview participants in this study.

P#	Age	Gender	Race	Occupation	Education
P1	25-34	Woman	–	Researcher	Doctorate degree
P2	35-44	Man	Asian	Portfolio Operator	Bachelor's degree
P3	25-34	Woman	Black	Social worker	Associate degree
P4	25-34	Woman	White	Teacher	Master's degree
P5	35-44	Woman	White	Manager	Bachelor's degree
P6	25-34	Man	Asian	Small business owner	Bachelor's degree
P7	35-44	Man	White	HR Systems Analyst	Master's degree
P8	35-44	Woman	Asian	Teacher	Master's degree
P9	25-34	Man	Asian	Marketing	Master's degree
P10	35-44	Woman	Asian	Finance manager	Master's degree
P11	18-24	Woman	White	Forensic Case Manager	Master's degree
P12	>65	Man	White	Retired	Master's degree
P13	55-64	Woman	White	Professor	Doctorate degree
P14	>65	Woman	White	Retired	Master's degree
P15	35-44	Man	White	Attorney	Doctorate degree
P16	45-54	Woman	White	Academic Advisor	Doctorate degree
P17	35-44	Man	White	Communications Manager	Master's degree
P18	>65	Man	White	Retired	Doctorate degree
P19	35-44	Man	White	Learning Specialist	Master's degree
P20	18-24	Man	Asian	Student	Some college, no degree

Table 1. Demographic information of interview participants. In the table, 'Education' represents the highest level of education that participants achieved and '–' refers to 'Prefer not to state'.