

# How Web Search Helps People Write Articles

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Current assisted writing techniques primarily provide linguistic and input supports such as grammar checking and sentence completion. But people also need knowledge and information-seeking assistance while writing articles. We examine such needs through a zoom-mediated “lab” user study. We ask expert and non-expert participants to write a 300-500 words article and allow them to use a web search engine freely throughout the process. Interview results disclosed the prevalence of using web search while writing an article and why web search helps or fails to help writing. The primary reasons include the effectiveness of the search engine for addressing the information needs, whether people have sufficient knowledge, and the type of information needed (factual or opinionated). Most participants also reported writing based on existing texts found from search results, including copying and pasting and paraphrasing, and the reasons for text reusing and referencing decisions. Our study provides an inspiring look for future research to provide automatic information-seeking and text reuse assistance for writing.

Additional Key Words and Phrases: assisted writing, knowledge support, information seeking, web search

## ACM Reference Format:

Shiyi He and Jiepu Jiang. 2018. How Web Search Helps People Write Articles. 1, 1 (February 2018), 10 pages. <https://doi.org/XXXXXXX.XXXXXX>

## 1 INTRODUCTION

Writing is not that easy, but a variety of techniques can help. For example, assisted writing technologies have offered various text composition supports widely used in messaging apps, emails, social media, and text editors over the past ten years. Previous studies have received much success in interactive writing [1, 4–6, 10, 14, 16, 21, 23–25, 28], text prediction [7, 8, 12, 17, 18], text correction [2, 27], and creative writing [3, 19, 20, 22, 26]. Although these studies significantly assisted people’s writing behaviors in many aspects, they focused mostly on providing interactive writing environments and improving communication efficiency. The research about providing knowledge and information-seeking assistance while writing an article is very limited.

We envision the next generation of assisted writing technologies to include both text composition supports and knowledge and information assistance—because we believe what underlies text writing is a series of information behaviors, including seeking, synthesizing, and reusing information and texts. As the very first step to studying this problem, we examine how people use web search engines to collect information and reuse texts while writing articles. We examine three specific research questions:

- RQ1: When and why does a search engine help writing?
- RQ2: When and why does a current search engine fail to help writing?

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Manuscript submitted to ACM

- RQ3: How do people reuse texts found in search results while writing articles?

We designed and conducted a zoom-mediated “lab” user study to answer these questions. We created a simulated writing task involving multiple requirements of different cognitive complexity levels following Bloom’s taxonomy of educational objectives [13] and Kelly et al.’s studies of search task complexity [11]. We asked participants to use a web search engine and finish the writing task and requirements. In the writing task, the participants could look for relevant information from a web search engine and reuse the texts they found in the results to help them write the articles. We interviewed these participants and analyzed their responses. We also recruited expert and non-expert participants (whose familiarity with the writing task varied greatly) and compared their results. The rest of this article introduces our experiment and findings.

## 2 RELATED WORK

Our study is relevant to previous work in assisted writing (including collaborative writing, predicted writing, and creative writing) and interactive information retrieval (e.g., how users interact with search engines to find information).

**Collaborative Writing:** Collaborative Writing aims to support online multi-person collaborative writing and remote interaction in people’s daily work. Many online collaboration work platforms, such as Google Docs, offer different ways of communicating and writing collaboratively. In addition, these tools can break language barriers to some extent. It helps people share knowledge and improve the quality of writing [1, 4–6, 10, 14, 16, 21, 23–25, 28].

**Predicted Writing:** Some text editors based on intelligent recommendation and text prediction technologies can assist people in writing from different aspects. For example, they identify the problems in format, spelling, grammar and provide sentence suggestions for correction and proofreading [2, 27]. Accordingly, some message interactive systems and online communities [12, 17] offer text suggestions based on people’s initial input to enrich and optimize expression in communication. Likewise, some email apps [18] offer reply suggestions according to the contents of email exchanges. Text prediction technologies are also widely used in more professional occasions, such as ensuring the words’ professionalism in technical documentation [7, 8]. In addition, they can standardize wording, maintain and manage consistency in articles. These technologies facilitate communication and improve the efficiency of information transmission.

**Creative Writing:** As the quality of AI-generated natural language texts improves [3], writing systems can offer suggestions by using natural language generation models to stimulate ideas and to support creative writing, enabling a fast, expressive, and creative writing experience. They support a variety of composing, including lyrics [26], multimedia stories, slogans [3, 19, 20], and data-driven articles [22]. However, studies on creative writing also have barriers to meeting users’ actual needs appropriately.

Our research is different from these previous studies in that we focus on people’s information-seeking behaviors and how they reuse the texts they found while writing articles. This also relates our work to earlier studies in interactive information retrieval, especially those comparing search behaviors with different tasks [9, 11, 15]. However, previous studies did not examine search behaviors under a writing scenario for the purpose of creating new texts. Thus, our study potentially sheds light on both research areas.

## 3 EXPERIMENT

We use a lab-based experiment to study how people seek information and reuse texts from search engines in writing. We designed a writing task according to Bloom’s taxonomy of educational objectives [13] and Kelly et al.’s work of search

Table 1. Bloom’s Taxonomy of Cognitive Process Dimensions [13].

Process	Definition
Remember	Retrieving, recognizing, and recalling relevant knowledge from long-term memory.
Understand	Constructing meaning from oral, written, and graphic messages through interpreting, exemplifying, classifying, summarizing, inferring, comparing, and explaining.
Apply	Carrying out or using a procedure through executing or implementing.
Analyze	Breaking material into constituent parts, determining how the parts relate to one another and to an overall structure or purpose through differentiating, organizing, and attributing
Evaluate	Making judgments based on criteria and standards through checking and critiquing.
Create	Putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure through generating, planning, or producing.

Table 2. Writing task description for participants (we removed the universities’ names for anonymity).

<b>Background:</b> You are a columnist writing for a magazine introducing graduate schools and programs in the United States. Your audience is those who want to apply for graduate schools.
<b>Task:</b> The editor asks you to write an article of 300-500 words introducing the Master of [anonymous] program at [anonymous] University. Your article needs to: <ul style="list-style-type: none"> <li>• introduce the admission requirement for this program and its ranking among similar programs in the US</li> <li>• introduce the expected jobs for this program’s graduates in the United States</li> <li>• compare this program’s curriculum at [anonymous] University with similar programs at peer schools, such as the University of [anonymous] and the University of [anonymous]</li> <li>• provide suggestions regarding who may benefit from this program at [anonymous] University</li> </ul>

Table 3. Writing Requirements and the Corresponding Cognitive Complexity Levels.

Process	Requirement
Remember	Introduce the admission requirements of this program and its ranking in the United States.
Understand	Introduce the expected jobs for this program’s graduates in the United States.
Analyze & Evaluate	Compare this program’s curriculum with similar programs at peer schools.
Create	Provide suggestions regarding who may benefit from this program.

task complexity [11]. We recruited participants to work on the task through Zoom-mediated experimental sessions. We interviewed participants and analyzed their responses. The rest of this section introduces our experimental design and interview process.

### 3.1 Writing Task

We design a writing task involving multiple requirements of different cognitive complexity levels to study how search engines help people finish these writing requirements.

Kelly et al. [11] introduced a popular method of designing search tasks with different cognitive complexity levels. They followed Bloom’s taxonomy of educational objectives [13] (Table 1) and categorized search tasks into the same six cognitive levels (remember, understand, apply, analyze, evaluate, and create). We follow a similar method to use Bloom’s taxonomy to design writing tasks requiring different cognitive complexity levels.

Table 2 shows the writing task. The task asks participants to write a 300-500 words article introducing a specific master’s program in a university in the United States. The writing task includes four detailed requirements (Table 3) linked to different cognitive process dimensions in Bloom’s framework (Table 1).

Table 4. Post-task Interview Questions.

Q1	Among the four requirements, for which one did you find the search engine <b>most helpful</b> while writing the article? Why?
Q2	Among the four requirements, for which one did you find the search engine <b>least helpful</b> while writing the article? Why?
Q3	While finishing this article, when and why did you feel it <b>necessary</b> to collect information from the search engine?
Q4	While finishing this article, when and why did you feel it <b>unnecessary</b> to collect information from the search engine?
Q5	While writing this article, did you compose your text based on existing text in the web pages you found? How? When did you do that?
Q6	While writing this article, did you make references to the web pages you found? Why and When did you do that?

The final task requirements displayed in Table 2 had undergone many changes through a pilot study involving nine users. We hoped to examine the influence of topic expertise on writing and searching behaviors. Thus, it is necessary to design a theme, which can efficiently recruit participants with distinct expertise levels. With this task, we can recruit current students enrolled in this program as expert participants and other students as non-expert participants. Also, we have revised the task requirements to ensure that most expert participants in the pilot study can finish them within 40 minutes in a lab-based environment.

### 3.2 Experimental Design

We conducted an online zoom-mediated “lab” user study asking participants to work on the writing task in Section 3.1. We experimented online through a zoom-mediated session to avoid potential health risks of participants during the COVID pandemic. The experiment had received institutional IRB approval.

The whole experiment session took about one hour to finish. During the experiment, we asked each participant to work on the same writing task with the help of the same web search engine (Google) for 40 minutes. Participants wrote articles in a browser using Google Docs, and they could open new tabs for web searches if needed. We did not encourage or restrict them to use web search engines specifically. Before they started writing, participants needed to fill out a pre-task survey. After they finished the writing task, they needed to fill out a post-task survey and finish an interview with us. Table 4 shows the interview questions, which correspond to our research questions. We audio-recorded the interview for later analysis.

We recruited 30 participants from the Internet. 15 of them are current students enrolled in the particular master’s program mentioned in the task (we refer to them as expert participants). The other 15 participants are students enrolled in educational programs of other disciplines (referred to as non-expert participants). To avoid the impact of language fluency on the experimental data, we required participants to be native English speakers and adults.

We compensated each participant at the rate of \$15 per hour. We also provided additional incentives to encourage participants to work better. We instructed them that experts would assess their articles regarding informativeness, accuracy, and coherence, and authors of the top 10% best-scored articles will receive a bonus of \$50.

### 3.3 Participants

We recruited two groups of participants (15 for each group). All participants are native English speakers aged between 18 and 30. The female-male ratios in expert and non-expert groups are 14:1 and 13:2, respectively. The non-expert

Table 5. Participants' responses for Q1 and Q3 regarding when and why a search engine helps writing an article.

	<b>Answer</b> (Options are not exclusive of each other)	<b>Total</b> <i>N</i> = 30	<b>Experts</b> <i>N</i> = 15	<b>Non-Exp.</b> <i>N</i> = 15	Cohen's $\kappa$	$\chi$ -square <i>p</i> value
Q1 task	<b>Remember</b> (admission & rank)	25	13	12	1.00	0.944
	<b>Understand</b> (expected jobs)	2	1	1		
	<b>Analyze &amp; Evaluate</b> (compare curriculum)	5	3	2		
	<b>Create</b> (who may benefit)	0	0	0		
Q1 reason	<b>none</b> (did not answer)	2	1	1	0.85	0.082
	<b>easy-to-find</b> (easy to find relevant pages)	21	7	14		
	<b>no-knowledge</b> (has no or little knowledge)	9	7	2		
Q3	<b>none</b> (did not answer)	1	0	1	0.83	0.018 *
	<b>easy-to-find</b> (easy to find relevant pages)	1	1	0		
	<b>no-knowledge</b> (has no or little knowledge)	21	8	13		
	<b>accurate</b> (ensure the accuracy of content)	13	10	3		
	<b>factual</b> (locate factual & specific information)	6	6	0		

participants' majors vary greatly, including, for example, education, medical science, law, business, engineering, etc. In general, there is no significant difference in other backgrounds (e. g., age and gender) between the two groups except their majors. However, we acknowledge that our participants are primarily female and may introduce biases.

#### 4 RESULTS

We report interview results to answer the three research questions. One primary annotator first developed a coding scheme after manually examining all participants' responses. Then, two annotators independently annotated the participants' responses according to the scheme. Tables 5, 6, and 7 summarize the findings. Note that participants may mention multiple reasons while answering a question, so the sum of people mentioning each option may exceed the total number of participants. We measure the two annotators' consistency using Cohen's  $\kappa$ —they have high consistencies in most questions ( $\kappa \geq 0.8$ ) and moderate ones for Q4 and Q6 (reason).

##### 4.1 RQ1: When and Why a Search Engine Helps Writing

Interview results disclose that a web search engine helps the most in the *Remember* tasks while people write articles. Experts and non-experts reported different reasons for using search engines to support writing. Table 5 summarizes the most salient reasons, including a lack of knowledge ("no-knowledge"), the effectiveness of search engines for addressing such tasks ("easy-to-find"), and locating accurate and factual information ("accurate" and "factual").

When answering Q1, 25 out of 30 participants responded that search engines helped the most in the *Remember* tasks, and the preference does not seem to vary much by expertise (13 for experts and 12 for non-experts). A few participants also mentioned the *Understand* and the *Analyze/Evaluation* tasks, but none mentioned the *Create* task. The reasons focus on the effectiveness of search engines for addressing the tasks ("easy-to-find") and the lack of knowledge to finish the content ("no-knowledge"). The distribution of these reasons did not vary significantly between experts and non-experts by a  $\chi$ -square test ( $p = 0.082$ ).

However, when asking when and why it was the most necessary to use the search engine while finishing the article (Q3), experts and non-experts responded with significantly different reasons ( $p = 0.018$ ). 10 out of 15 expert participants expressed the need to use the search engine to ensure the information they provided is accurate ("accurate"), while only 3 out of 15 non-experts mentioned a similar reason. Besides, 6 out of 15 experts said they felt it necessary to rely on

Table 6. Participants' responses for Q2 and Q4 regarding when and why a current search engine fails to help writing an article.

	<b>Answer</b> (Options are not exclusive of each other)	<b>Total</b> <i>N</i> = 30	<b>Experts</b> <i>N</i> = 15	<b>Non-Exp.</b> <i>N</i> = 15	Cohen's $\kappa$	$\chi$ -square <i>p</i> value
Q2 task	<b>Remember</b> (admission & rank)	2	2	0	0.87	0.424
	<b>Understand</b> (expected jobs)	5	2	3		
	<b>Analyze &amp; Evaluate</b> (compare curriculum)	10	6	4		
	<b>Create</b> (who may benefit)	18	8	10		
Q2 reason	<b>none</b> (did not answer)	2	2	0	0.82	0.210
	<b>cannot-find</b> (cannot find relevant pages)	21	8	13		
	<b>enough-knowledge</b> (to write w/o search)	3	2	1		
	<b>does-not-need</b> (does not need to search)	4	3	1		
Q4	<b>none</b> (did not answer)	6	1	0	0.66	0.083
	<b>cannot-find</b> (cannot find relevant pages)	3	1	2		
	<b>enough-knowledge</b> (to write w/o search)	12	7	5		
	<b>does-not-need</b> (does not need to search)	6	3	3		
	<b>opinionated</b> (locate opinionated content)	5	5	0		

search engines to locate factual information ("factual"), but none of the non-experts mentioned a similar reason. Some example responses are as follows:

**B10:** "The search engine has a lot of websites, and the websites have accurate and correct information which students would like to know."

**A12:** "I found it necessary for concrete details, like when I wanted to find the admissions requirements and the rankings. I wanted something like numbers, and not who may benefit from this program and stuff that's sort of like a subjective answer."

Overall, the top reason for using a search engine while writing an article is the lack of knowledge to finish the content (21 out of 30 participants reported "no-knowledge"). More non-experts mentioned this reason than expert participants (13 out of 15 versus 8 out of 15). Moreover, among the eight experts reporting this reason, one specifically mentioned that they knew something already but wanted to know more, and two said they hoped to use the search engine to double-check the accuracy of their knowledge.

**A04:** "I definitely had to look rankings and admission requirements up. It was helpful to just look those up because I kind of know them, but I wasn't sure about the specifics. So I wanted to make sure I was getting the exact information."

**A10:** "I kind of feel like I relied on the search engine to verify information, even if it was stuff that I already know. For example, I know that the program requires 39 credits, and I felt like I had to find it on the website."

#### 4.2 RQ2: When and Why a Current Search Engine Fails to Help Writing

In contrast, interview results show that the current web search engine we used for our study helped the least with the *Create* and *Analyze/Evaluation* tasks. The most salient reasons are also about people's knowledge, the effectiveness of search engines for addressing the tasks, and the types of information people need, which are highly consistent with participants' responses for Q1 and Q3. Table 6 reports the findings.

When answering Q2, 18 out of 30 participants responded that the search engine helped the least with the *Create* task, and 10 out of 30 said the *Analyze/Evaluate* task. The distributions of the responses do not differ significantly by expertise ( $p = 0.424$ ). Regarding the reasons, most participants mentioned the limited effectiveness of search engines

Table 7. Participants' responses for Q5 and Q6 regarding reusing texts and making references.

	<b>Answer</b> (Options are not exclusive of each other)	<b>Total</b> <i>N</i> = 30	<b>Experts</b> <i>N</i> = 15	<b>Non-Exp.</b> <i>N</i> = 15	Cohen's $\kappa$	$\chi$ -square <i>p</i> value
Q5	<b>Yes</b> (reused texts, e.g., copy, paraphrase) <b>No</b> (did not reuse texts in search results)	28 2	13 2	15 0	0.93	0.464
Q5 reason	<b>none</b> (did not answer) <b>accuracy</b> (to keep the exact wording) <b>time</b> (faster to copy & paste) <b>appropriate</b> (make texts appropriate) <b>knowledge</b> (reuse due to limited knowledge) <b>plagiarism</b> (not reuse to avoid plagiarism)	6 10 4 3 4 3	3 6 4 1 1 1	3 4 0 2 3 2	0.84	0.397
Q6	<b>Yes</b> (made references) <b>No</b> (did not make reference)	20 10	12 3	8 7	0.93	0.245
Q6 reason	<b>none</b> (did not answer) <b>source</b> (providing the information source) <b>moreinfo</b> (a link for more details) <b>time</b> (did not reference due to limited time)	5 13 11 8	1 7 7 5	4 6 4 3	0.60	0.396

for finishing these tasks (21 out of 30; "cannot-find"), indicating that current web search engines might not support the *Create* and *Analyze/Evaluate* tasks well.

**A06:** "For the part about who might benefit from the program, I kind of like I just answered that based on all the people I've met in my life. I'm in 30 years so I've met a lot of people while writing this."

When asking when and why the search engine is the least necessary while writing an article (Q4), 12 out of 30 participants mentioned that they had sufficient knowledge ("enough-knowledge"). 5 of 30 also said they felt a search engine could not help with tasks requiring opinionated or subjective information ("opinionated"). We note that these 5 participants are experts, while no non-expert participants mentioned the type of information as a reason when answering Q4. However, the distributions of responses did not show significant differences between experts and non-experts by a Chi-square test ( $p = 0.083$ ).

#### 4.3 RQ3: How People Reuse Texts Found in Search Results While Writing Articles

Our interview results also disclosed the prevalence of reusing texts found from search engines while writing articles and the various reasons and ways for reusing. Table 7 reports the findings.

For Q5, 28 out of 30 participants expressed that they composed texts based on the texts found in search results, including 22 mentioned they had copied and pasted some texts, and 10 said they had paraphrased the texts. The distribution of responses did not differ significantly between experts and non-experts ( $p = 0.464$ ).

Participants mentioned various reasons for reusing texts found in search results, and the distribution did not vary significantly by experts and non-experts either ( $p = 0.397$ ). 10 out of 30 mentioned they copied and pasted some texts from the results to be accurate in their articles ("accurate"), e.g., keeping the exact wording. 4 out of 30 said that sometimes they felt copying texts would be faster than typing on their own ("time"). 4 participants mentioned knowledge-related reasons ("knowledge"), such as they felt easier to write based on existing texts than purely by their own. Some example responses are as follows:

**A04:** "Yes, there was one point where I definitely just copied and pasted the admissions requirements from the web page. Because that seems to make the most sense to put the exact words here of what they were looking

*for. Sometimes I copied and pasted titles and longer names of things to save time."*

**B06:** *"... I literally just copied and pasted that. Then I rephrase it down below, like I paraphrased it and then deleted the original one."*

Moreover, responses for Q5 also disclosed when people found it appropriate or inappropriate to reuse the texts in their articles. For example, two participants mentioned that they would shorten the original texts to make them more readable in their articles. One said she would reuse the texts only when she felt the original texts were appropriate for the article. Three mentioned that they did not reuse the texts to avoid plagiarism.

Participants also responded to their reasons for making references while writing articles (Q6). Among the 30 participants, 20 mentioned that they did make references in their articles. Their responses disclosed two reasons for referencing. 13 out of 30 hoped to provide a source for the information, such as to be persuasive ("source"). Besides, 11 out of 30 said that they hoped to provide a link such that readers may explore more details if needed ("moreinfo"). Also, 8 participants mentioned that they wanted to make references but did not have enough time.

**B08:** *"As being someone that's not an expert in the field, I use the ability to cite something to emphasize my opinions; it had a more substantial basis underneath it."*

**A04:** *"... just because I didn't want to include all of it. I just want to include a small amount of information enough that the reader who's reading this article would get a general sense. But then they could go to the actual page and read the full requirements for things like admissions requirements."*

## 5 DISCUSSION AND CONCLUSION

Our study and interview results have disclosed people's needs to seek information and reuse texts from existing sources while writing articles. We found that it is prevalent to seek information while writing articles due to the perceived lack of knowledge, and thus web search becomes a necessary tool to fulfill such needs. Also, participants reported that they perceived current web search engines could effectively address some but not all types of information needs—many expressed that search engines helped locate factual information and address the *Remember* task, but are less useful for more complex ones such as the *Create* and *Analyze/Evaluate* tasks. In addition, participants also reported widespread needs for reusing texts found in the search results and the reasons (such as to save time and be accurate). Moreover, we found experts' and non-experts' responses have some differences, although they are primarily consistent.

These findings help illuminate the design of future automatic assisted writing tools providing information seeking and text reuse supports, which require a combination of information retrieval, natural language processing, and HCI techniques. First, we believe it would be necessary to provide information search functionalities in assisted writing platforms to facilitate the widespread information-seeking needs of writers directly. Second, current web search engines fail to provide after-search support, such as helping people extract and reuse texts from search results. We envision future assisted writing systems to provide such support and the ability to help people paraphrase and tailor the texts to avoid ethical concerns. Third, we believe it is beneficial to make such assisted writing systems personalized and adaptive to help better different writers (with distinct expertise levels) and various writing contexts.

However, we also acknowledge certain limitations of our study, which may influence the generalizability of the findings. First, we have only designed a single writing task and a limited number of requirements. We expect the results to vary if the task changes or if people write other types of articles. Second, we conducted the experiment in a lab-based setting which may largely differ from a naturalistic setting. Also, despite being the only choice during the pandemic, Zoom experiments may influence the results, as one participant reported that she did not copy and paste texts as she



felt inconvenient doing during a Zoom remote control session. Third, we used a convenient sampling method, and our participants have some biases, especially regarding the female-male ratio. We expect future studies to further verify and enrich our findings.

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